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Climate Change Impacts and Adaptation in Swiss Cereal Production: Integrating Biophysical and Economic Modeling

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Abstract

Because agriculture is intimately linked to climate, it is the most vulnerable economic sector to climate change. Thus, agricultural production systems will be affected by expected changes in climatic conditions over the next decades and century. These changes comprise, in general, elevated CO2 concentration, higher temperatures, altered precipitation and transpiration regimes and an increased frequency of climatic extreme events. Because agriculture causes a variety of benefits and problems, impacts of climate change on agricultural systems are of importance from an economic but also from a social and environmental point of view. Moreover, the assessment of impacts and potential adaptation supports the decision making processes of farmers, governments, and other stakeholders. This thesis addresses impacts and adaptation to climate change in maize and winter wheat production at the Swiss Plateau. In particular, this thesis aims to assess climate change impacts taking farmers' incentives to adapt to both changing climatic conditions and potential changes in socioeconomic conditions into account. An overview over different approaches of modeling climate change impacts on crop production as well as a review of studies that analyze climate change impacts on Swiss agriculture are given in the introductory chapter 1.

Chapter 2 describes the evaluation of three functional forms and two estimation methods for the estimation of crop production functions, which are the linkage between biophysical and economic models. It shows that exceptional crop yield observations (outliers) can cause misleading results if least squares regression is applied for the estimation of these functions. In order to address this problem, robust regression techniques are applied that are not affected by such outliers. The use of robust regression narrows the range of optimal input levels across different functional forms and reduces potential costs of misspecification compared to least squares estimation. Thus, differences between functional forms are reduced by applying robust regression.

In chapter 3, an approach that integrates the biophysical model CropSyst in an economic model is used to analyze the impact of climate change on Swiss maize and winter wheat production. Adaptation options such as changes in sowing dates, changes in production intensity, and the adoption of irrigation farming are considered in the model. Assuming

different climate change and price scenarios, it shows that farmers' adaptation actions and crop yields are sensitive to both climate change and output prices. The latter is particularly important for Swiss crop production because decreases in crop prices due to market liberalization are expected to be large. Accordingly, the effects of market liberalization might outweigh climate change induced effects on crop production. Moreover, model results show that the considered adaptation measures are sufficient to generate higher and less variable crop yields in the future.

Chapter 4 investigates the impact of climate change on the profitability of site specific technologies in Swiss maize production. Site specific technologies are characterized by input application taking spatial variability across the field into account and the adoption of this management option can reduce environmental pollution and negative externalities caused by common agricultural practice. It shows that climate change increases the differences in optimal input application and yield variability between soils with different contents of soil organic matter. This leads, ceteris paribus, to higher incentives for the adoption of site specific technologies in the future.

In chapter 5, the economic potential of irrigation as an adaptation option to climate change in Swiss maize farming is analyzed. Three climate change scenarios (covering the time horizon 2030-2050) and two future price scenarios are considered. In addition, the economic viability of irrigation farming in future climate is analyzed with respect to changes in water prices. For rainfed maize production, the impact of climate change on yield levels is small but yield variability increases. Even though the adoption of irrigation leads to higher and less variable maize yields in the future, economic benefits of this adoption decision are expected to be rather small. Thus, no shift from the currently used rainfed system to irrigated production is expected in the future.

In general, not the expected changes in climatic conditions but rather changes in institutional arrangements and market conditions will influence the adaptation decisions taken by the farmers' and future developments in the Swiss cereal production. Moreover, future technological development and the future structure of agri-environmental policies might also far outweigh climate change induced effects on Swiss cereal production.

Zusammenfassung

Landwirtschaft ist direkt von klimatischen Bedingungen abhängig und deshalb einer der ökonomischen Sektoren, die am anfälligsten auf Änderungen in diesen Bedingungen reagieren. Klimawandel wird deshalb die zukünftige Struktur und Produktivität landwirtschaftlicher Systeme beeinflussen. Erwartete Änderungen in den klimatischen Bedingungen der nächsten Dekaden umfassen unter anderem, steigende CO2 Konzentrationen und Temperaturen, sich ändernde Niederschläge, sowie häufigeres Auftreten von Extremereignissen. Die erwarteten Auswirkungen des Klimawandels auf landwirtschaftliche Systeme sind von grosser ökonomischer, sozialer aber auch umweltrelevanter Bedeutung, da landwirtschaftliche Aktivitäten auf verschiedenste Art und Weise in diesen Bereichen Nutzen, Leistungen aber auch Probleme hervorrufen. Erkenntnisse über erwartete Auswirkungen sowie über mögliche Anpassungsmassnahmen können ausserdem die Entscheidungsprozesse von Landwirten, staatlichen Entscheidungsträgern und anderen involvierten Akteuren unterstützen. In dieser Arbeit werden Auswirkungen des Klimawandels und potentielle Anpassungsmassnahmen im Mais- und Winterweizenanbau des Schweizer Mittelandes analysiert. Dabei ist es ein besonderer Bestandteil dieser Analyse, sowohl die Anreize des Landwirtes sich ändernden klimatischen Bedingungen anzupassen als auch sich ändernde sozioökonomische Bedingungen zu berücksichtigen. Das einleitende Kapitel 1 diskutiert verschiedene Modellierungsansätze zur Bestimmung von Auswirkungen des Klimawandels auf den Pflanzenbau und gibt einen Überblick über Studien die die Auswirkungen des Klimawandels auf die Schweizer Landwirtschaft analysieren.

Kapitel 2 beschreibt die Evaluierung von drei Funktionstypen und zwei Regressionsverfahren zur Schätzung von landwirtschaftlichen Produktionsfunktionen, welche das Bindeglied zwischen biophysikalischen und ökonomischen Modellen darstellen. Ungewöhnliche Ertragsbeobachtungen (Ausreisser) können zu irreführenden Resultaten führen, wenn kleinste Quadrate Regression zur Schätzung der Produktionsfunktionen verwendet wird. Deshalb werden zusätzlich robuste Regressionsmethoden verwendet, welche nicht durch Ausreisser beeinträchtigt werden. Im Vergleich zur kleinsten Quadrate Schätzung führt die Verwendung robuster

Regressionsmethoden zu kleineren Unterschieden zwischen den optimalen Input-Empfehlungen die aus den verschiedenen Funktionstypen abgeleitet werden und reduziert somit die potentiellen Kosten durch Misspezifizierung. Durch die Verwendung robuster Regressionsmethoden werden Unterschiede zwischen verschiedenen Funktionstypen deutlich reduziert.

Kapitel 3 beschreibt einen Modellierungsansatz, der das biophysikalische Modell CropSyst und ein ökonomisches Modell miteinander verbindet um Auswirkungen des Klimawandels auf die Schweizer Mais- und Winterweizenproduktion zu bestimmen. In diesem Modell werden veränderte Saattermine, veränderte Produktionsintensität sowie der Einsatz von Bewässerung als Anpassungsmassnahmen berücksichtigt. Unter Verwendung verschiedener Klimawandel- und Preisszenarien zeigt sich, dass sowohl zukünftige Erträge als auch die Anpassungsentscheidungen des Landwirtes stark von den Annahmen über zukünftige Klimabedingungen und Preise abhängen. Es zeigt sich, dass eine eventuelle Marktliberalisierung, die zu grossen Änderungen in landwirtschaftlichen Preisniveaus in der Schweiz führen würde, die Effekte des Klimawandels aufwiegen kann. Die Modellresultate zeigen ausserdem, dass die hier berücksichtigten Anpassungsmassnahmen ausreichen, um in der Zukunft höhere sowie weniger variable Erträge in der Mais- und Winterweizen Produktion zu erreichen.

In Kapitel 4 werden die Auswirkungen des Klimawandels auf die Rentabilität teilflächenspezifischer Produktionssysteme im Schweizer Maisanbau analysiert. Diese Produktionssysteme zeichnen sich durch einen Inputeinsatz aus, der Unterschiede innerhalb eines Feldes berücksichtigt und somit zu einer Reduzierung von Umweltverschmutzung und anderer negativer Externalitäten führen kann. Es zeigt sich, dass Klimawandel die Unterschiede zwischen unterschiedlich fruchtbaren Böden bezüglich optimalem Inputeinsatz und Ertragsvariabilität erhöht. Dadurch steigen, ceteris paribus, die Anreize der Landwirte in Zukunft teilflächenspezifischer Produktionssysteme einzusetzen.

Kapitel 5 analysiert die ökonomischen Potentiale von Bewässerung als Anpassungsmassnahme an den Klimawandel im Schweizer Maisanbau unter Berücksichtigung von drei Klimawandelszenarien für den Zeitraum 2030-2050 und zwei Preisszenarien. Zusätzlich wird der Einfluss von Änderungen im Wasserpreis auf die

Wirtschaftlichkeit von Bewässerung in zukünftigen Klimabedingungen analysiert. Die Auswirkungen des Klimawandels auf die Ertragsniveaus sind gering, jedoch steigt die Ertragsvariabilität im unbewässerten Maisanbau. Obwohl der zukünftige Einsatz von Bewässerung zu höheren und stabileren Erträgen führt, bleibt die Wirtschaftlichkeit dieser Systeme relativ gering. Daher wird auch unter zukünftigen klimatischen Bedingungen kein grossflächiger Wechsel vom heutigen unbewässerten Maisanbau zu bewässerter Produktion erwartet.

Es zeigt sich jedoch, dass erwartete Anpassungsentscheidungen der Landwirte und die zukünftigen Entwicklungen in der Schweizer Getreideproduktion eher durch die Änderungen im institutionellen und ökonomischen Umfeld als durch die Änderungen klimatischer Bedingungen beeinflusst werden. Des Weiteren können auch technologischer Fortschritt und die zukünftige Ausgestaltung agrarumweltpolitischer Massnahmen die Effekte des Klimawandels deutlich aufwiegen.

Contents

Chapter 1

Introduction

Agriculture is the most vulnerable economic sector to changes in climatic conditions because it is "intimately linked to climate" (Kandlikar and Risbey, 2000). Even though agriculture is only of small economic importance[1] in the developed world, it attracts special attention in political and public discussions[2] because it provides multiple societal and environmental benefits: Agricultural activities contribute, for instance, to food security, socio-economic development of rural areas, conservation of cultural heritage, and to the preservation of environmental functions and habitats (Hediger and Lehmann, 2007). In contrast, agricultural activities also cause negative consequences such as the degradation of environmental systems, and are a major source of climate-relevant emissions (Baldock et al., 2000, Hungate et al., 2003, Tilman, 1999). Thus, impacts of climate change on agricultural systems are of importance from an economic but also from a social and environmental point of view. Furthermore, the analysis of climate change impacts on agriculture is important to improve knowledge on both future food supply and future land use (e.g., Ewert et al., 2005, Gregory et al., 2005, Olesen and Bindi, 2002, Rounsevell et al., 2005). Information on these expected impacts can support the decision making processes of farmers, governments, and other stakeholders on strategic planning and agricultural policy implementation.

In this thesis, assessment of climate change impacts and adaptation measures is made for winter wheat and maize production at the Swiss Plateau, the major production region for cereals in Switzerland. Winter wheat and maize are the most important winter- and spring-sown cereals, respectively, currently covering about 90000 and 17000 hectares in Switzerland (SBV, 2007). Besides their national importance, these crops are often used as "reference crops" to assess impacts of climate change on crop production (e.g., Ewert et al., 2005) because maize and wheat are among the most important crops for human and

[1] In Switzerland, the total annual agricultural production amounts to about 10 Billion Swiss Francs (BfS, 2008).
[2] See Mann (2003) for an introductory note on the role of agricultural policy in Switzerland, and Aföldi and Tutkun-Tikir (2007) for media coverage on the topic of agriculture in Switzerland.

animal nutrition worldwide. Therefore, the choice of these crops allows for comparability with results of other studies.

This chapter is organized as follows: A brief discussion on changes in climatic conditions is given in section 1.1. Thereafter, impacts of climate change on agriculture and different approaches to project these impacts are discussed in section 1.2. Section 1.3 briefly discuss the role of adaptation in climate change impact modeling, and section 1.4 reviews the literature on climate change impacts on Swiss agriculture. Finally, the introduction concludes with the objectives and the outline of this thesis.

1.1 Climate Change and Climate Extremes

In the definition of the Intergovernmental Panel on Climate Change (IPCC, 2007a), climate change

> *"…refers to any change in climate over time, whether due to natural variability or as a result of human activity. This usage differs from that in the United Nations Framework Convention on Climate Change, where climate change refers to a change of climate that is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and that is in addition to natural climate variability observed over comparable time periods".*[3]

Accordingly, henceforward in this thesis the term 'climate change' is used without any specification of its causes and origin as well as without any valuation of mitigation measures and impacts that are beyond the scope of this thesis.

Expected changes in climatic conditions over the next decades and century comprise, in general, elevated CO2 concentration, higher temperatures, altered precipitation and transpiration regimes and increased frequency of extreme climatic events[4] (Easterling et

[3] In addition, the term 'climate' might require a proper definition: "Climate in a narrow sense is usually defined as the average weather, or more rigorously, as the statistical description in terms of the mean and variability of relevant quantities over a period of time ranging from months to thousands or millions of years. The classical period for averaging these variables is 30 years, as defined by the World Meteorological Organization. The relevant quantities are most often surface variables such as temperature, precipitation and wind. Climate in a wider sense is the state, including a statistical description, of the climate system." IPCC (2007a).

[4] The term climatic extreme event might comprise droughts, storms, heat waves, cold spells, or heavy rainfalls (see Beniston and Stephenson, 2004, for examples). In some cases – but not necessarily – such climatic extreme events might cause "economic" extreme events such as in the insurance and finance sector whose definitions are highly case dependent. Note that a formal definition of extreme events is difficult or

al., 2007). In Europe, annual mean temperatures are expected to increase more than at the global mean. But, projected annual and seasonal changes of temperature as well as precipitation widely differ between northern Europe and the Mediterranean (Christensen et al., 2007). In addition, the occurrence of climate extreme events in Europe will be altered by climate change. Heat waves, for instance, are expected to increase in frequency, intensity and duration. Moreover, droughts and heavy rainfalls are expected to occur more frequently in the future (Christensen et al., 2007).

For the Swiss Plateau region – located north of the Alps – projections based on the simulations of Frei (2005) are employed in this thesis (see Chapter 3 for details). In these projections, temperature increases in all seasons and these increases are expected to have the largest magnitude in summer. Precipitation is expected to decrease in summer and autumn, but to rise in winter. Changes in spring rainfalls are ambiguous. Moreover, these simulations show that the magnitudes of the projected seasonal changes in temperature and precipitation are highly uncertain[5] (see also Gyalistras et al., 1998). In order to take these uncertainties into account, different climate change scenarios (instead of a single scenario assumption) that reflect different levels of CO2 concentrations and magnitudes of seasonal changes in climatic conditions are used in this thesis. The projections employed in this thesis represent scenarios for the time slices around 2030 and 2050.

On the global and regional scale, agricultural production might have been already influenced negatively by changes in climatic conditions within the last decades as it is indicated, for instance, by Lobell and Asner (2003), Lobell and Field (2007), Peng et al. (2004), and Tao et al. (2006). For Switzerland, Beniston (2007) showed that in the last years, anomalous warm periods in all seasons of the year have broken long term records. But, analyzing the period 1961 to 2006, the observed leveling-off of cereal yields in Switzerland since the 1990s is rather caused by agri-environmental policy reforms than

even impossible, because "…there are too many non-mathematical factors which have an influence on the meaning of the above word(s)." (Embrechts and Schmidli, 1994).

[5] In general, major sources of these uncertainties are model and emission uncertainties. Thus, projections might differ depending on the choice of global and regional climate models as well as the choice of the emission path (see Christensen et al., 2007, and Knutti 2008a,b for details). To explore and represent these projection uncertainties, the climate scenarios employed in this thesis are based on ensemble simulations using different global and regional climate models and two emission scenarios (A2 and B2) within the scope of the PRUDENCE project (see Frei, 2005, for details). For the time horizon of 2030-2050 that is employed in this thesis, model uncertainties are expected to outweigh emission uncertainties, which might be vice versa if longer time horizons are considered.

by climatic changes (Finger, 2008a). Moreover, no increases of relative yield variability[6] in the last decades are identified in this study. Thus, the impacts of recent climatic changes on crop yields are expected to be not yet severe in Switzerland.

However, the more frequent occurrence of climatic extreme events, their impacts on production in the primary sector, and their role of being prospect for expected climatic changes in the future have deserved special attention in the last years (e.g., Beniston, 2004, Beniston and Goyette, 2007, Calanca, 2007, Jolly et al., 2005, and Luterbacher et al., 2004). In particular, the heat and drought in summer 2003 caused low crop yields in Switzerland and in throughout Europe (Ciais et al., 2005). The reduction of crop yield was particularly large for spring sown crops, such as maize, that had not terminated growth by the time of the heat wave. In contrast, other (in particular winter sown) crops had terminated growth by time of the heat wave and were thus less affected by the 2003 summer drought (Ciais et al., 2005). Taking the economic losses of this heat and drought into account and seeing the summer of 2003 as "a shape of things to come" (Beniston, 2004), this necessitates the identification of potential climate change impacts on Swiss crop production in the future.

1.2 Climate Change Impacts on Crop Production and Modeling Aspects

In order to assess potential impacts of climate change on agricultural systems, several modeling approaches have been proposed, which are briefly introduced and discussed in this section. On the one hand, changes in mean and variability of climate variables such as temperature and precipitation might directly affect the plant and thus crop yield levels, yield variability and crop quality. On the other hand, climate change might induce indirect effects that also affect crop production. These indirect effects comprise, for instance, changes in nutrient leaching, turnover of soil organic matter, as well as changes in weed, insect, disease pressure, and several potential interactions of these effects. Reviews and discussions on these indirect effects are given in Easterling et al., 2007, Fuhrer 2003, 2006, and Olesen and Bindi, 2002. In addition, climate change is expected to have (direct and/or indirect) impacts on socioeconomic conditions of agricultural

[6] Relative yield variability is expressed as the ratio of yield variability and the yield level.

production such as input- and output prices, trade patterns as well as migration (e.g., Darwin, 2004, Easterling et al., 2007, Fischer et al., 2005, Juliá and Duchin, 2007, Parry et al., 2005, Perch-Nielsen et al., 2008, Reilly et al., 1994).

The (direct) impact of climatic changes on crop yields and crop yield variability, which is considered in this thesis, can be assessed using different modeling approaches. These approaches might be (roughly) classified in biophysical models, regression models, and integrations of both approaches[7]. Projected crop- and location-specific impacts might be input for further assessment models that analyze changes in land-use, trade patterns and price levels (e.g., Darwin, 2004, Ewert et al., 2005, Fischer et al., 2005, Juliá and Duchin, 2007, Reilly et al., 1994, Rounsevell et al., 2005).

Biophysical models (also the terms crop growth models and process-based models are used frequently) describe explicitly several above- and below-ground processes that follow biophysical and biochemical mechanisms. An overview of different models and model components is given in Meinke et al. (2001), Stöckle et al. (2003), and Tubiello and Ewert (2002). These processes are driven by crop management, weather data and information on site- and crop-specific characteristics. Thus, these models enable the integration of scenarios on future climate to assess its impacts on crop production. Biophysical models are used to analyze climate change impacts on crop production, for instance, in Challinor et al. (2004), Donatelli et al. (2002), Eitzinger et al. (2003), Holden and Brereton (2006), Mearns et al. (1997), Osborne et al. (2007), Torriani et al. (2007a), and Tubiello et al. (2000, 2002)[8].

The advantage of biophysical models is the explicit formulation of physiological processes and their interactions, which allows for a good description of a climate-plant relationship even if the analyzed scenarios exceed current production and climatic conditions. Moreover, changes in crop management practices such as irrigation, fertilizer application, tillage intensity or crop rotation, can be implemented as potential adaptation strategies in these models. However, biophysical models do not address economic

[7] Other modeling approaches (that are beyond the scope of this brief discussion) comprise, for instance, indirect approaches to model impacts of climate change such as Ricardian (i.e. hedonic) models – see Mendelson et al. (1994) for an example and Kandlikar and Risbey (2000) as well as Schneider et al. (2000) for critical discussions on this approach.

[8] A review of climate change impact studies using biophysical models (for the period 1995-2002) is given in Tubiello and Ewert (2002).

incentives of the farmers if considering adaptation to climate change. Thus, these models have an "…apparent inability to adequately simulate ways in which farm management and markets can affect yield and returns…" (Risbey et al., 1999). Due to these limitations, these models are often employed to analyze impacts of climate change on potential yields (i.e., no input factors are limiting) or to analyze these impacts by assuming that all factors (e.g. crop management) but climatic conditions remain unchanged.

Regression models predominantly use observed data on the field-, farm, regional- or national scale that contain information on crop yield, crop management, and mean and variability of climate variables such as temperature and rainfall. These data sets are used to estimate a relationship between crop yields and climatic variables. In addition, also the relationship between climatic variables and crop yield variability can be analyzed with these models. In order to assess impacts of climate change on crop yield levels or crop yield variability, the estimated relationships are extrapolated assuming changes in the considered climate variables. Regression models are used to analyze impacts of climate change, for instance, in the studies of Chen et al. (2004), Isik and Devadoss (2006), Flückiger and Rieder (1997), Lobell (2007), Lobell et al. (2008), McCarl et al. (2008), Parry et al. (2004), and Tao et al. (2008).

In comparison to biophysical models, the set-up of such models for a certain location is – given the availability of the necessary data – much easier. In addition, regression models captivate with high traceability and intuitive interpretability. If historical data is used, these models already comprise adaptation actions taken by the farmers to past changes in climatic conditions and thus avoid the overestimation of negative climate change effects on crop production. However, new, innovative adaptation options cannot be examined with the extrapolation of historical data. Hence, these models are rather suitable for short-term than for long-term projections. Regarding the applicability of the regression models for long-term projections, Goodwin (2008) summarizes his criticisms – unequivocally – as follows: "Yield data from yesterday … may not tell us a great deal about yields in 2050". Moreover, models based on historical data are not able to effectively capture future crop-climate relationships because crop physiological aspects are not considered and the variation in climatic variables in the observed period is usually low. In addition, these models allow not for an integration of the CO2 fertilization effect[9] and its interaction with other climatic and management variables (e.g. Antle and Capalbo, 2001, Tubiello and Ewert, 2002).

In order to overcome drawbacks of both biophysical and regression models, combinations of these modeling approaches are applied to assess climate change impacts on crop production. For instance, simulations with a biophysical model are re-parameterized in the usual form of regression models (e.g. Iglesias et al., 2000) or are used to parameterize a few (i.e. less than in the biophysical models) crop physiological processes (e.g. Torriani et al., 2007b)[10]. Therefore, these approaches use meta-analyses of biophysical simulations in order to benefit from the simplicity and straightforward applicability of regression models, but to retain basic crop-physiological components that broaden the applicability of these models (Torriani et al., 2007b).

The modeling approach employed in this thesis also uses meta-analysis of biophysical models and is "at the interface between crop science and economy" (Odening et al., 2008). In this approach, biophysical simulations are used to estimate production and yield variation functions that are simple analytical descriptions of yield and yield variability responses to agricultural inputs such as nitrogen and irrigation water. These functions are used to integrate these biological response processes in an economic allocation model. Similar meta-modeling approaches that integrate biophysical and economic modeling have been applied, for instance, to analyze agri-environmental policy measures (e.g., Brugger, 2008). This approach inherits the good descriptions of crop physiological processes from the biophysical models and can furthermore integrate (socio-)economic

[9] Increasing CO2 concentrations might have a fertilization effect on crop yields because "Crops sense and respond directly to rising CO2 through photosynthesis and stomatal conductance…" (Long et al., 2006, see also Allen et al., 1996, and Körner et al., 2007, for details). However, especially the quantification of these effects on crop yields is highly uncertain (e.g., Körner et al., 2007). In particular the CO2 fertilization effects as implemented in most biophysical models – such as CropSyst that is employed in this thesis – might be overestimated (see Long et al., 2006, for details). Thus, "the effect of elevated carbon dioxide (CO2) on crop yields is one of the most uncertain and influential parameters in models to assess climate change impacts and adaptations" (Lobell and Field, 2008).

[10] In addition, regression models can be improved by integrating concepts of biophysical models, such as growing degree days, in the regression equations (e.g., Schlenker and Roberts, 2008).

aspects (e.g., input- and output-prices, farmers' risk aversion) in climate change impact assessments[11].

The final choice of a certain class of models clearly depends on the available (particularly data-) resources, on the addressed spatial (leaf, canopy, field) and temporal (minutes, days, seasons) scales (Tubiello and Ewert, 2002), as well as on the individual preferences and methodological backgrounds of researchers. However, the consideration of changes in socio-economic conditions in any assessment of climate change impacts is necessary because those factors are expected to determine how climate change will affect agriculture (FAO, 2002). In addition, the implementation of adaptation – or the assessment of potential adaptation options – is indispensable in climate change impact modeling as it is outlined in the subsequent section. Thus, the potential to integrate both adaptation options and changes in socio-economic conditions motivated the choice of modeling approach that is employed in this thesis and is presented in chapter 3.

1.3 Agricultural Adaptation to Climate Change

Adaptation to climate change can be defined as an "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities." (IPCC, 2007b). Accordingly, the objective of adaptation to climate change is "to reduce vulnerability to climate change and variability, thereby reducing their negative impacts." (Stern, 2007).

These definitions do not comprise information on the initiators (who is doing the adaptation), time scales (short- vs. long-term), and regional scales (farm- vs. national-level) of adaptation actions. For agricultural systems, these specifications of adaptation options might be classified as follows: Potential initiators are farmers, governments, and other stakeholders. Different time scales might include time horizons of a season, multiple years or multiple decades, which implies tactical- (e.g., adjust management operations to current weather), strategic- (e.g., investment in an irrigation system) and

[11] A more advanced class of empirical economic production models "that can be linked to site-specific biophysical models for use in integrated assessment research" – such as climate change impact assessment (e.g., Antle et al., 2004) – has been proposed by Antle and Capalbo (2001) but is beyond of the scope of this section.

structural (e.g., breeding of new varieties) adaptation decisions, respectively (Risbey et al., 1999). Finally, these adaptation measures might address the field- (e.g., adjusting tillage intensity), farm- (e.g., diversification of on- and off-farm activities), regional- (e.g., a large scale irrigation project) or national level (e.g., a national insurance program). Different agricultural adaptation options as well as time- and regional-scales are presented and discussed in Kandlikar and Risbey (2000), Olesen and Bindi (2002), Risbey et al. (1999), and Smit and Skinner (2002).

This thesis focuses on farmers' strategic adaptation to climate change at the field level. In particular, shifts in sowing dates, the strategic adjustment of the production intensity as well as the adoption of irrigation farming and site specific management practices are considered. Even though our approach uses static analysis for different climate scenarios, we are aware that farming activities and particularly adaptation are continuous processes. For instance, by assuming a shift in sowing dates of two weeks in our analysis for a time slice around the year 2050, we assume that sowing dates will be adjusted continuously with changing climatic conditions over time.

The implementation of adaptation in climate change impact models is necessary to derive meaningful results. The continuous adaptation to environmental conditions, for instance in breeding and crop management, has been always a substantial part of farming activities (Evans, 1997). Thus, the inclusion of "dumb farmers" (Schneider et al., 2000) or "naive farmers" (Kandlikar and Risbey, 2000) – i.e., any adaptation is excluded from the analysis – is a rather unrealistic assumption. However, some studies do not address adaptation at all and thus (whether intended or not) conclude massive negative impacts of climate change on agriculture.

In contrast some models assume "clairvoyant" farmers "blessed with perfect foresight" (Schneider et al., 2000). Many, in particular economic, approaches often assume optimal decision making that is rare in the real world and thus only an idealized version of reality (Kandlikar and Risbey, 2000). Therefore, these approaches overestimate the adaptation potential of farmers and other stakeholders and accordingly underestimate negative impacts of climate change. The approach that is applied in this thesis assumes farmers to have perfect knowledge of production systems, i.e. of production and yield variation functions. However, we do not expect an underestimation of climate change impacts in our results because the scope of potential adaptation options that are considered in this thesis is very limited. But, existing models should be improved (and thus approximate the description of real world behavior) by taking the complexity of adaptation decisions into account. In conclusion, the consideration (or non-consideration) of adaptation options in climate change impacts models is crucial for the results derived with these models and should be taken into account if conclusions and policy recommendations are drawn from these results.

1.4 Climate Change Impacts on Swiss Agriculture

For Switzerland, there is – compared to other countries – only a limited number of studies that analyze climate change impacts on agriculture[12]. Even though some of these (Swiss case-) studies are briefly mentioned and discussed in later chapters, this section provides an extended overview of the literature.

Grassland production is one of the most important agricultural activities in Switzerland and covers about 70% of the agricultural acreage (SBV, 2007). Therefore, climate change impacts on grassland production are essential for the future development of Swiss agriculture, even though climate change impact studies are often restricted to crop production. Calanca and Fuhrer (2005) show that Swiss grassland production will benefit from elevated CO2 concentrations and more favorable temperature and radiation conditions, leading to potential increases of total grassland production in the range of about 50%. This positive response of grassland systems to the expected changes in climatic conditions is supported by different regional impact studies in Switzerland (e.g., Riedo et al., 1999, 2000, 2001). However, even though average productivity is increasing, these effects are site-specific and climate change, particularly drought events, might (negatively) affect grassland composition towards weed species and thus reduce fodder quality (Stampfli and Zeiter, 2004, Gilgen and Buchmann, 2008).

Potential impacts of the altered occurrence of climatic extreme events such as droughts, heat waves, and heavy precipitation on agricultural (and silvicultural) systems in

[12] This excludes studies at the global or European scale that include Switzerland representing only a few grid points without taking specific climatic, soil, and production conditions into account.

Switzerland are discussed in Fuhrer et al. (2006). An increasing frequency of heavy rainfalls is expected to increase problems of soil erosion and risks of flooding. However, climate warming might reduce current production constraints due to waterlogged soils. The more frequent occurrence of droughts and heat waves is concluded to increase risks of losses in crop yields and forage quality. In addition, Fuhrer et al. point out an increasing weed pressure in forage production due to the increased frequency of drought events.

Impacts on Swiss crop production are analyzed by Flückiger and Rieder (1997) using a regression model for barley, maize, potato and winter wheat. Yield data from 490 farms over 15 years as well as monthly temperature and precipitation data are used to estimate a relationship between yield levels and these weather variables. By assuming climate change scenarios, the extrapolation of these relationships leads to large reductions in yield levels that range from -6% (potatoes) to -29% (barley). In addition, yield increases due to the CO2 fertilization effect are added in the projections of Flückiger and Rieder that finally outweigh negative effects of climate change for all crops but maize. These projections are integrated in a sectoral model for the Swiss agriculture and are analyzed simultaneously with potential effects of a free-trade agreement on Swiss agriculture. Taking both factors into account, Flückiger and Rieder conclude that not climate change but market liberalization is the major source of future changes in Swiss agriculture.

Using Monte-Carlo simulations, Lips et al. (2008) analyze the impact of climate change on the costs and risks in winter wheat harvest at the eastern Swiss Plateau. Climate change is expected to improve harvest conditions because rainy days occur less frequent in mid-summer. Hence, climate change reduces, ceteris paribus, drying costs and problems of outgrowth. Accordingly, the harvest machinery capacity can be reduced and climate change might thus lead to a reduction of harvest costs by up to 23%.

Torriani et al. (2007b) analyze the impact of climate change on Swiss maize productivity and associated production risk using a stochastic yield growth model that is parameterized with simulations from a biophysical model. In their simulations, Torriani et al. considered “rather drastic changes” in climatic conditions but no adaptation options except of an anticipation of the growing season (i.e. earlier sowing). It shows that climate change causes a decrease of yield levels, an increase of yield variability and a considerable increase of farmers' production risk.

Torrinai et al. (2008) used the yield model developed in Torriani et al. (2007b) to evaluate the effectiveness of weather derivatives as an adaptation option to climate change in Swiss maize production. It shows that production risk increases considerably due to climate change, but also due to the non-consideration of adaptation options. However, Torriani et al. show that risk hedging using weather derivatives (a precipitation based index is used) can reduce production risk and is thus an effective instrument to cope with climate change induced risk increases in maize production.

The biophysical model CropSyst is used by Torriani et al. (2007a) to analyze the impact of climate change on the mean and variability of potential yields in maize, winter wheat and winter canola production in Switzerland. Without considering any adaptation measure, climate change leads to decreasing yield levels and increasing yield variability for all crops. Taking additionally the CO2 fertilization effect into account, future winter wheat yields are expected to exceed current levels, and climate change induced decreases in crop yields are much smaller for maize and winter canola. Torriani et al. show that breeding is a viable adaptation strategy because larger thermal time requirements (i.e. growing degree days) lead to higher yield levels for all crops in the future. In addition, earlier sowing and irrigation lead to higher yield levels and lower relative yield variability in maize farming. Therefore, adaptation measures such as breeding, irrigation and shifts in sowing dates might reduce or even outweigh climate change induced effects on crop yields and crop yield variability. However, both the adoption of irrigation farming and shifts in sowing dates do not alter yields in winter wheat and winter canola production.

In conclusion, the here presented studies suggest that impacts of climate change on Swiss agriculture are ambiguous[13] and that these impacts are site-, crop-, and scenario specific. Yet, these studies indicate that the impact of climate change on grassland production and

[13] Differences in the results of some studies arise, for instance, from differing modeling approaches, time horizons studied, climate scenarios used, and differing assumptions on the CO2 fertilization effect (e.g., the assumed fertilization effect for maize and doubled CO2 concentrations ranges from 0% in Torrinai et al., 2007b, to about 20% in Flückiger and Rieder, 1997).

winter-sown crops might be rather positive but negative for spring sown crops[14]. However, changes in socioeconomic conditions are not considered in all studies but Flückiger and Rieder (1997), and some of these studies do not take adaptation measures adequately into account. This thesis aims to fill these gaps by taking different adaptation measures as well as changes in socioeconomic conditions into account when analyzing climate change impacts on Swiss cereal production.
The climate change impact and adaptation studies presented in the chapters 3 to 5 of this thesis are an extension of the modeling approach presented in Torriani et al. (2007a). Based on the biophysical model CropSyst, an economic model component is added to enable the simultaneous analysis of several adaptation options taking farmers' economic incentives in reactions to expected climatic and market stimuli into account.

1.5 Objective and Outline

In general, the aim of this thesis is to analyze impacts and potential adaptation to climate change on maize and winter wheat production at the Swiss Plateau. To this end, a modeling approach that combines a biophysical and an economic model is applied. More specifically, the following research questions are addressed in this thesis:

- Which functional form and which estimation technique are most suitable to estimate maize production functions that are the linkage between biophysical simulations and economic modeling?
- What are the impacts of climate change on maize and winter wheat production at the Swiss Plateau if simple adaptation measures are taken into account?
- How important are impacts of climate change on crop production in the future compared with effects that are caused by decreasing price levels due to market liberalization?

[14] The ambiguity and high uncertainties of impact studies are – of course – not unique to Swiss case studies. Lobell and Burke (2008) summarize the occurrence of high uncertainties in impact estimates and the associated problems as follows: "Estimates of climate change impacts are often characterized by large uncertainties that reflect ignorance of many physical, biological, and socio-economic processes, and which hamper efforts to anticipate and adapt to climate change."

- Is the impact of climate change soil-specific and thus leads to an increasing profitability of site specific crop management systems?
- Is irrigation an (economic) viable adaptation option in Swiss maize farming?

The dissertation is organized in six chapters. Four of these chapters (Chapters 2-5) address the research questions outlined above and have already been published or are submitted for publication. Therefore, these chapters are presented in the form of self-contained papers. The detailed outline is as follows:

- Chapter 2 (Finger and Hediger, 2008) describes the evaluation of different functional forms and estimation methods for the estimation of crop production functions. These production functions are the linkage between the biophysical and the economic model that are employed in our model. Thus, the correct specification and estimation of these functions is the prerequisite for the analyses that are presented in the subsequent chapters.
- Chapter 3 (Finger and Schmid, 2008) presents a modeling approach that integrates a biophysical and an economic model to assess climate change impacts on crop production. Taking into account simple adaptation options, numerical examples are given for maize and winter wheat production at the Swiss Plateau. In addition, different price scenarios are considered in order to take potential price changes due to market liberalization into account.
- Chapter 4 (Finger and Gerwig, 2008) applies the model to analyze soil specific impacts of climate change on maize production. Furthermore, the impact of climate change on the profitability of site specific management practices is evaluated.
- Chapter 5 (Finger et al., 2008) applies the model to analyze the economic potential of irrigation as an adaptation option to climate change in Swiss maize farming. In this chapter, three climate change and three future price scenarios are considered. In addition, the impact of changes in water prices on the economic viability of irrigation farming as an adaptation option is analyzed.

- Chapter 6 summarizes the main results and redraws the main conclusions of the thesis and gives an outlook on possible future research directions.

Chapter 2

The application of robust regression to a production function comparison

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Key words: production function estimation, production function comparison, robust regression, crop response

Abstract

The adequate representation of crop response functions is crucial for agronomic as well as agricultural economic modeling and analysis. So far, the evaluation of such functions focused on the comparison of different functional forms. In this article, the perspective is expanded by also considering different regression methods. This is motivated by the fact that exceptional crop yield observations (outliers) can cause misleading results if least squares regression is applied. In order to address this problem we also apply robust regression techniques that are not affected by such outliers. We evaluate the quadratic, the square root and the Mitscherlich-Baule function using the example of Swiss corn (*Zea mays* L.) yields. It shows that the use of robust regression narrows the range of optimal input levels across different functional forms and reduces potential costs of misspecification compared to least squares estimation. Thus, differences between functional forms are reduced by applying robust regression.

2.1 Introduction

The adequate representation of production or crop yield functions is crucial for modeling purposes in agronomic, agricultural and environmental economic analyses. The discussion and estimation of different functional forms has therefore gained much attention in agronomic and agricultural economics literature. Various functional forms have been considered so far, but less attention has been given to the estimation techniques in general and the impact of exceptional crop yield observations (outliers). The latter is important since the Least Squares (LS) fitting criterion can produce misleading results if data sets contain outliers, such as exceptional yields caused by extreme weather events or climate situations. In order to address this problem we apply robust regression techniques that are not affected by such outliers. The aim of this article is to analyze the influence of estimation techniques on the evaluation of different functional forms that describe crop responses. This extends the literature on the comparison of different functional forms (e.g. Ackello-Ogutu et al., 1985, Alivelu et al., 2003, Bélanger et al., 2000, Frank et al., 1990, Llewelyn and Featherstone, 1997) by taking the effect of outliers for the estimation and evaluation of crop production functions into account.

So far, comparison of functional forms has been based on the coefficient of determination (e.g. Alivelu et al., 2003), residual distribution (e.g. Bélanger et al., 2000), non-nested hypothesis testing (e.g. Frank et al., 1990) and potential misspecification costs (e.g. Llewelyn and Featherstone, 1997), respectively. Using LS and robust regression, we devote special attention to the cost of misspecification which constitutes an economic approach to the comparison of production functions. This allows us to assess the potential underestimation of net revenues that would arise from using calculations based on LS instead of robust regression methods or from an improper specification of the functional form.

We apply a meta-modeling approach that makes use of crop yield data generated with a biophysical simulation model to estimate and compare crop production functions. Biophysical simulation allows us to generate an enlarged data base compared with field observations. It particularly enables the creation of comprehensive data sets of crop yields with respect to the variation of analyzed factors such as agricultural inputs, while keeping other factors constant. The resulting data set is used to estimate different types of crop production functions. Those are subsequently integrated in a non-linear economic optimization model to assess optimal factor inputs, such as nitrogen fertilizer and irrigation water. Numerical examples are given for Swiss corn (*Zea mays L.*) yields.

2.2 Material and Methodology

2.2.1 Production Functions

Three types of crop production functions are analyzed in this study: two polynomial specifications (the quadratic and the square root function) and the Mitscherlich-Baule function. These functional forms are frequently used in the literature and proved to accurately capture the underlying relationships (Ackello-Ogutu et al., 1985, Anderson and Nelson, 1975, Berck and Helfand, 1990, Frank et al., 1990, Fuchs and Löthe, 1996, Heady and Dillon, 1961, Jalota et al., 2007, and Llewelyn and Featherstone, 1997, Rajsic and Weersink, 2008, Yadav et al., 2003).

Being aware that corn yields are driven by numerous factors, we focus our analysis on two crucial production factors: nitrogen fertilizer and irrigation water. Following Llewelyn and Featherstone (1997), production functions are used to describe corn yield responses to nitrogen and irrigation water in a simple analytical description, which is necessary to represent yield response processes in agricultural and environmental economic allocation models. These functions implicitly consider other production factors such as soil and climate (Godard et al., 2008). In contrast, complex production functions — e.g. including sets of climate variables and their interactions with management variables — can complicate or preclude straightforward application in further economic analysis. Therefore, we focus in this study on simple analytical forms of production functions that are widely used in practice (e.g. Hexem and Heady, 1978, Finger and Schmid, 2008, Fuchs and Löthe, 1996, Godard et al., 2008, Medellín-Azuara et al., 2008, and Rajsic and Weersink, 2008, Tsur and Dinar, 1997).

The *quadratic form*, shown in equation (2.1), consists of an additive composition of the input factors, their squared values, and an additional interaction term. The latter elucidates whether the input factors are independent of each other or not. The quadratic function is formally defined as follows:

$$Y = \alpha_0 + \alpha_1 \cdot N + \alpha_2 \cdot W + \alpha_3 \cdot N^2 + \alpha_4 \cdot W^2 + \alpha_5 \cdot N \cdot W \qquad (2.1)$$

Y denotes corn yield per area, N the amount of inorganic nitrogen applied, and W irrigation water applied. The α_i's are parameters that must satisfy the subsequent conditions in order to ensure decreasing marginal productivity of each input factor: $\alpha_1, \alpha_2 > 0$ and $\alpha_3, \alpha_4 < 0$. Furthermore, if $\alpha_5 > 0$ the two input factors are complementary. They are competitive if $\alpha_5 < 0$, while $\alpha_5 = 0$ indicates independence of the two input factors.

The *square root function* (equation 2.2) is very similar to the quadratic form but produces different shapes of the curves. The square root form is defined as follows:

$$Y = \alpha_0 + \alpha_1 \cdot N^{1/2} + \alpha_2 \cdot W^{1/2} + \alpha_3 \cdot N + \alpha_4 \cdot W + \alpha_5 \cdot (N \cdot W)^{1/2} \qquad (2.2)$$

To ensure decreasing marginal productivity of each input factor, the parameters must satisfy the same conditions as for the quadratic form, and their interpretation is identical.

The *Mitscherlich-Baule function* (equation 2.3) allows for a growth plateau, which follows from the von Liebig approach to production functions. Moreover, this functional form is characterized by continuously positive marginal productivities of the input factors. It does not exhibit negative marginal productivities, as the above polynomial forms. Formally, the Mitscherlich-Baule function is given by

$$Y = \alpha_1 \cdot (1 - \exp(-\alpha_2 \cdot (\alpha_3 + N))) \cdot (1 - \exp(-\alpha_4 \cdot (\alpha_5 + W))) \qquad (2.3)$$

with α_1 representing the growth plateau, and α_3 and α_5 the natural input endowments, that include nitrogen in the soil (α_3) and water endowments (α_5) such as soil moisture.

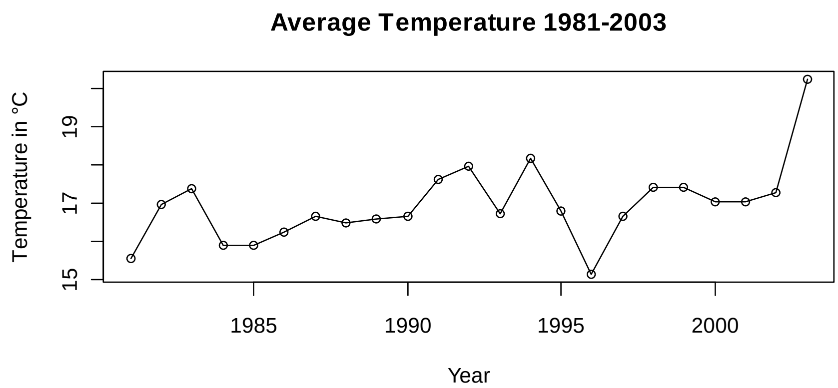
The coefficients α_2 and α_4 describe the influence of the corresponding input factors on the yield. Unlike the classical von Liebig production function, the Mitscherlich-Baule function allows for factor substitution. It is not linear limitational in the input factors as the von Liebig function, i.e. the isoquants are not right-angled.

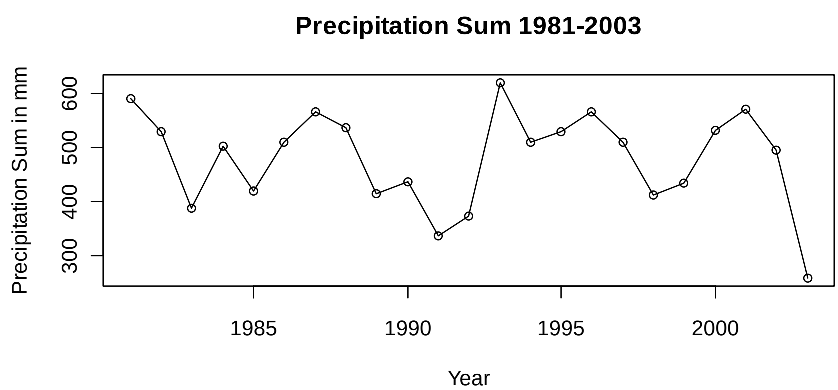
2.2.2 Data

Our analysis and estimation of production functions is based on simulated corn yield data that is generated with the CropSyst model. This is a deterministic crop yield simulation model that has been widely used and validated (see Stöckle et al., 2003, for a review of studies using CropSyst). It involves various above and below ground processes, such as soil water budget, soil-plant nitrogen budget, crop phenology, canopy and root growth, biomass production, crop yield, residue production and decomposition, and soil erosion by water. These processes are simulated with daily time step. The model is calibrated to field trials and sample data. Model settings and calibration for the Swiss Plateau region are presented in Torriani et al. (2007a).

In our analysis, CropSyst is driven by daily weather data from six different locations on the Swiss Plateau for the years 1981 – 2003, as provided by the Swiss Federal Office of Meteorology and Climatology (MeteoSwiss). These locations are distributed over the eastern Swiss Plateau ranging from 06°57' to 08°54' longitude and are located at elevation levels between 422 and 565 meter above sea level (Finger and Schmid, 2007). Compared to an approach with one single location, the use of observations from six different weather stations broadens the database and allows us to represent production functions for a large proportion of the entire Swiss corn producing acreage. Growing season average temperatures and precipitation sums (average over the six locations) for the period 1981-2003 are shown in Figure 2.1.

Figure 2.1 Growing season average temperatures and precipitation sums: 1981-2003





To enable meta-modeling analysis and avoid distortions due to dynamic effects, all simulations are conducted using identical starting conditions. Accordingly, the simulation and subsequent data analysis are restricted to one uniform type of soil for all locations, characterized by texture with 38% clay, 36% silt, 26% sand and soil organic matter content at 2.6% weight in the top soil layer (5 cm) and 2.0% in lower soil layers (Torriani et al., 2007a). Moreover, the type of management is uniform for all simulations. Identical seeding dates, irrigation settings (possible from day one after sowing to harvesting, never exceeding field capacity), fertilizer type (inorganic nitrogen fertilizer) and fertilizer application dates are used in CropSyst (Finger and Schmid, 2007). This approach avoids distortions due to non-uniform soil and management properties.

To have a comprehensive data set, one simulation is conducted without application of fertilizer and irrigation for each location and each year. Additional combinations of irrigation and fertilizer are generated randomly. Taking nitrogen fertilizer application rates from 0 to 320 kg/ha and irrigation water from 0 to 340 mm, this results in 212 different levels of nitrogen application to the plants and 60 different levels of irrigation.

The resulting dataset consists of 527 observations. Assuming a dry matter content of 85%, average yields for three different ranges of irrigation *W* and fertilizer *N* application, respectively, are shown in Table 2.1. This rough approximation of the average corn yields reveals a global yield maximum for $71 \leq W \leq 140$ and $76 \leq N \leq 150$. Simulated corn yields decrease if the amounts of irrigated water or applied fertilizer deviate from those input ranges.

Table 2.1: Average simulated corn yields (kg/ha) 1981-2003

		Applied nitrogen in kg/ha		
		0-75	**76-150**	**151-320**
Applied irrigation water in mm	**0-70**	6955	8872	8521
	71-140	7293	9717	9100
	141-340	7275	8814	9158

Source: CropSyst simulations.

In our meta-modeling approach, output of the biophysical model is restructured into crop production functions. As a consequence, key relationships among the factors studied that are relevant for aggregate economic analysis can be isolated on a yearly basis (Jalota et al., 2007). In contrast, processes in the biophysical model are conducted on a daily time step. Thus, the relationships estimated in the crop production functions do not replicate settings in the biophysical model, i.e. in the data generating process. Similar meta-modeling approaches that combine biophysical simulations and economic modeling by using production functions are used, for instance, by Jalota et al. (2007), and Llewelyn and Featherstone (1997).

Due to settings in the crop yield simulation, the dataset contains quasi-continuous input-output combinations. In contrast to discrete application of inputs, the use of quasi-continuous input levels enables a regression approach rather than an analysis of variance. Moreover, the random application of inputs allows for unbiased estimation of the production function coefficients since input levels are uncorrelated with other variables, such as environmental factors, that also influence corn yields but are not considered in the production function estimations.

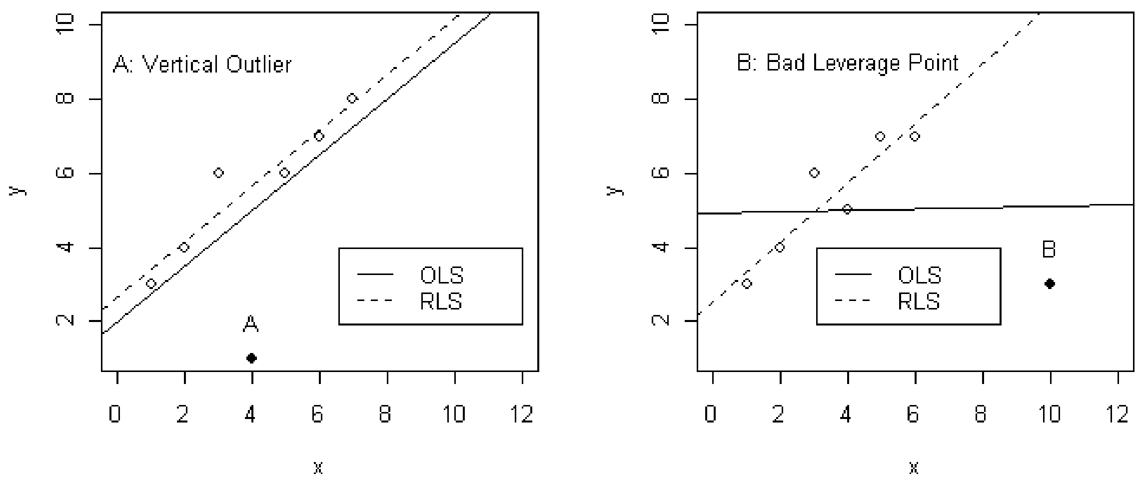
2.2.3 Outliers and Estimation Methodology

Exceptional climatic years are supposed to cause exceptional crop yield levels and to have an extraordinary influence on plant response to irrigation and fertilization. For instance, heat waves, droughts or waterlogged soils can indirectly restrict yield levels. Furthermore, the plants are expected to respond specifically to input management under extreme climatic conditions. As a consequence, they may involve outliers that deviate from the relationship described by the majority of the data and thus lead to a misspecification of the estimated production function.

The least squares estimator can not cope with a single outlier because one outlier can be sufficient to move the coefficient estimates arbitrarily far away from the actual underlying values. As a consequence, outliers cause unreliable coefficient estimates if LS is applied (e.g. Hampel et al., 1986, Hubert et al., 2004, and Rousseeuw and Leroy, 1987).

Two standard examples for outliers in a linear simple regression model are presented in Figure 2.2. Point A clearly deviates from the typical linear relationship between the dependent (y) and the independent (x) variable. Such 'vertical' outlier is characterized by an unusual observation in the dependent variable. The impact of vertical outliers on the LS estimation of regression coefficients is usually small and mainly affects the regression intercept (Sturm and de Haan, 2001). If unusual observations occur in the set of independent variables, these outliers are called leverage points. If such leverage point deviates from the linear relationship described by the majority of observations it is called 'bad leverage point' such as Point B in Figure 2.2. Due to the exposed position of the outlier it has a leverage effect on the LS coefficient estimation. In contrast, a leverage point is called 'good leverage point' if it does not deviate from the typical relationship. Good leverage points are no outliers and even improve the regression inference as these points reduce standard errors of coefficient estimates.

Figure 2.2. Examples for outlying observations.



Note: Regression lines are fitted using least squares (LS) and reweighted least squares (RLS). Source: According to Sturm and de Haan (2001).

Reliable regression results are provided if and only if outliers are removed or appropriately down-weighted. But, various classical methods for outlier detection, suffer from a lack of robustness (see Maronna et al., 2006, Rousseeuw and Leroy, 1987, for details). For instance, outliers can tilt the (original) regression line and have small regression residuals. As a consequence, outliers might not be discovered in residual plots (Sturm and de Haan, 2001). Furthermore, studentized and jackknifed residuals, Cooks distances and other diagnostics based on Hat matrix elements, for instance, are susceptible to the so called masking effect (Rousseeuw and Leroy, 1987). If more than one outlier occurs, these outlier diagnostics might not be able to detect a single outlier because one outlier can be masked by the presence of others. Moreover, high dimensionality of the estimation problem and a large number of observations as it is the case for our analysis can make graphical outlier identification procedures infeasible.

In contrast, robust regression enables reliable coefficient estimation also in presence of outliers, and is therefore applied in this study. In particular, reweighted least squares (RLS) regression is used for the estimation of the quadratic and the square root production functions (equations 2.1 and 2.2). It is favored here over other robust regression methods (e.g. the MM-estimator) due to its good robustness and efficiency properties as well as because of the better interpretability of indicated outliers

(Rousseeuw and Leroy, 1987). RLS is a weighted LS regression, which is based on an analysis of least trimmed squares (LTS) regression residuals. The LTS-estimator is a high-breakdown estimator that can cope with outlier contamination of up to 50%. Based on the idea of trimming the largest residuals the LTS fitting criterion is defined as follows:

$$\underset{\hat{\beta}}{Min} \sum_{i=1}^{h} (r^2)_{i:n} \tag{2.4}$$

$(r^2)_{(i)}$ are the ascending ordered squared (robust) residuals and h is the so-called trimming constant. In our analysis, $h = \left[(3n + p + 1)/4\right]$ is employed (Rousseeuw and Van Driessen, 2000), with p denoting the number of coefficients that are estimated.

The computation of LTS coefficients follows an algorithm described in Rousseeuw and Leroy (1987). Due to the low efficiency of LTS estimation, it is only used for outlier identification. An observation is identified as an outlier if the absolute standardized robust residual ($\left|r_i / \hat{\sigma}\right|$) exceeds the cutoff value of 2.5, with r_i and $\hat{\sigma}$ denoting the (robust) LTS residuals and scale estimates, respectively. This cutoff-value choice is motivated by a (roughly) 99% tolerance interval for Gaussian distributed standardized residuals (Sturm and de Haan, 2001). With X representing the matrix of independent variables and Y the vector of the dependent variable, coefficient estimates of RLS regression are defined as follows:

$$\hat{\beta}_{RLS} = \left(X'WX\right)^{-1} X'WY \tag{2.5}$$

The diagonal elements of the weighting matrix ($W = diag\left\{w_1, \ldots, w_n\right\}$) are generated by the indicator function, $I_{Outlier}$, that generates weights of zero for observations that are identified as outliers and weights of one otherwise:

$$w_i = I_{Outlier}\left[\left|\frac{r_i}{\hat{\sigma}}\right| \leq 2.5\right] \qquad (2.6)$$

RLS regression is applied for coefficient estimation of quasi linear functional forms, using the ROBUSTREG procedure in the SAS statistical package (SAS Institute, 2004). An example for the better robustness properties of RLS compared to LS is indicated in Figure 1. LS coefficient estimates change in the presence of outliers, in particular for bad leverage points. In contrast, RLS coefficient estimates are not affected by outliers in this example.

Because LTS regression is not suitable for nonlinear problems such as the Mitscherlich-Baule function (equation 2.3), non-linear regression approaches are required. Robust regression is implemented in this case by using iteratively reweighted least squares (IRLS). In order to reduce the influence of outliers on estimation results, weights are generated with M-estimation using Tukey's biweight (Hampel et al., 1986) such as shown in equation (2.7). These weights are re-estimated at each step of iteration until convergence.

$$w_i = \begin{cases} (1-(r_i / \hat{\sigma} \cdot c)^2)^2, & |r_i / \hat{\sigma}| \leq c \\ 0, & |r_i / \hat{\sigma}| > c \end{cases} \qquad (2.7)$$

r_i is the (robust) IRLS residual, $\hat{\sigma}$ the (robust) scale estimate and c a tuning constant. Following Hogg (1979), we employ the median of absolute deviations from the median (MAD) for robust scale estimation and set the tuning constant to 5.0. In contrast to LTS, IRLS is no high breakdown estimation technique. In order to validate results, we conduct sensitivity analysis of crucial factors such as starting values and tuning constant. We use the Levenberg-Marquardt algorithm that ensures stable estimation for highly correlated coefficient estimates that occur in our analysis (Schabenberger et al., 1999). In this study the nonlinear Mitscherlich-Baule function is estimated with IRLS using the NLIN procedure in the SAS software package.

Besides the most important property of giving trustworthy coefficient estimates, robust regression provides detailed insight in the structure of the data. If LS and robust regression results are considerably different and many outliers are identified, the related observations have to be examined. Above all, the interpretation of outliers is indispensable. Ruling out that outliers are caused by typing, copying or measuring errors, this interpretation should take not only statistical but mainly reasons from the agronomic point of view into account. Thus, in the following, all estimations are conducted with both least squares and robust regression and outlier interpretation is provided.

2.3 Results

2.3.1 Estimation Results

Within our dataset, the year 2003 involves the largest number of observations identified as outliers. About 25% of the observations that are identified by the RLS method as outlier or are given very small weights in the IRLS method, can be attributed to this particular year[15]. It is characterized by high temperatures and low precipitation in the relevant seeding-to-harvest period that caused particularly low corn yields in all Europe (Ciais et al., 2005). Other years with exceptionally low levels of precipitation and high temperatures during the corn growing season (e.g. 1983, 1991) also frequently occur in the lists of outlying observations.

The reason for the existence of outliers in these years is twofold. First, the yield levels are lower than usually. Second, the relationship between independent and dependent variables is affected by different reactions to input levels in situations where one of the inputs is a limiting factor. The yield response to irrigation water is higher than usual if – unlike in normal years – water constitutes a limiting factor for the plants in the Swiss Plateau. Furthermore, the interaction between fertilizer and irrigation water is higher because the plants' response to nitrogen also highly depends on water availability as nitrogen is taken up by the roots in a water solution.

Table 2.2 presents the estimation results for the quadratic and the square root production functions, respectively. The coefficient α_5 (Applied Nitrogen * Irrigation Water) is not

[15] In total RLS identifies 43 outliers for the quadratic production function and 37 for the square root function. Moreover, 36 observations have weights smaller than 0.25 in the IRLS estimation of the Mitscherlich-Baule function.

significantly different from zero in the four estimated polynomial functions. This indicates that rainfall is sufficient to ensure efficient nitrogen uptake under normal climatic conditions in Switzerland.

Table 2.2: Coefficient estimates for the quadratic and the square root production functions

Variable	Least Squares	Reweighted Least Squares
	Quadratic production function (equation 2.1)	
Intercept	6638.27 (165.05)**	6661.42 (179.24)**
N	25.64 (17.62)**	27.55 (22.71)**
W	6.05 (5.62)**	5.58 (5.75)**
N^2	-0.071 (12.22)**	-0.0724 (14.94)**
W^2	-0.018 (3.87)**	-0.0162 (3.88)**
NW	0.0078 (1.51)	0.0037 (0.89)
adj. R^2	0.57	0.71
	Square root production function (equation 2.2)	
Intercept	6589.99 (155.02)**	6601.92 (162.13)**
$N^{1/2}$	297.18 (12.42)**	313.09 (16.34)**
$W^{1/2}$	75.09 (4.26)**	67.14 (4.17)**
N	-11.22 (6.88)**	-10.54 (8.15)**
W	-3.03 (2.40)*	-2.5 (2.17)*
$(NW)^{1/2}$	1.46 (1.43)	0.36 (0.45)
adj. R^2	0.58	0.73

Note: Statistics in parentheses are t statistics. (**) and (*) indicate significance at the 1% level and 5% level, respectively.

The Mitscherlich-Baule production function estimates are presented in Table 2.3. It shows that the coefficient estimates for irrigation water and water endowment (α_4 and α_5) are not significantly different from zero at the level of five percent in the LS estimation. In contrast, the coefficients α_4 and α_5 are significant at the one percent level if robust regression (IRLS) is used. Moreover, the coefficient estimate for α_5 increases remarkably if IRLS regression is applied. This is explained by the fact that mainly dry years are excluded or down-weighted in the robust regression, such that the estimated soil water endowment is higher for the remaining observations.

Table 2.3: Coefficient estimates for the Mitscherlich-Baule production function

Variable	Least Squares	Iteratively Reweighted Least Squares
α_1	9180.6 (95.14)**	9410.3 (87.7)**
α_2	0.0288 (5.72)**	0.0266 (7.38)**
α_3	50.6952 (5.96)**	48.3036 (7.75)**
α_4	0.0598 (1.22)	0.0304 (2.95)**
α_5	45.14 (1.24)	71.22 (3.10)**
adj. R^2	0.74	0.81

Note: Statistics in parentheses are t statistics. (**) indicates significance at the 1% level.

Yet, the decision on the most appropriate estimation technique cannot exclusively be based on statistical measures. For instance, the goodness of fit cannot be compared between different estimations because the deletion of outliers, by definition, increases the goodness of fit for the regression on the remaining observations. Hence, conclusions on the appropriateness of functional forms and estimation techniques can be drawn if and only if the misspecification costs are calculated and interpreted, as shown in the subsequent section.

2.3.2 Optimal Input Levels and Costs of Misspecification

The analysis of production functions usually involves an assessment of optimal input and output levels, which is generally determined through maximization of a suitably defined objective function. For the purpose of our analysis, this is given by the subsequent profit function

$$\pi = P_{Corn} \cdot f(W, N) - P_{Nitrogen} \cdot N - P_{Irrigation} \cdot W \qquad (2.8)$$

where the net return (or quasi-rent) per hectare π is equal to the gross return (crop price P_{Corn} times corn yield $f(W,N)$), minus total nitrogen costs (nitrogen price $P_{Nitrogen}$ times amount of nitrogen applied N) and total irrigation costs (irrigation price $P_{Irrigation}$ times amount of irrigation water W) per hectare. For simplicity, other costs are assumed to be constant and therefore irrelevant for calculating the profit maximizing input combination. By maximizing the above profit function (equation 2.8), the optimal input levels are determined through the following first-order conditions, where N^* and W^* are the profit maximizing input levels of nitrogen fertilizer and irrigation water, respectively:

$$\frac{\partial f(W,N^*)}{\partial N} = \frac{P_{Nitrogen}}{P_{corn}} \text{ and } \frac{\partial f(W^*,N)}{\partial W} = \frac{P_{Irrigation}}{P_{corn}} \qquad (2.9)$$

These conditions are satisfied if the input price equals the value marginal product of each production factor; i.e., the crop price multiplied by the factor's marginal productivity for each input factor.

In the further analysis, we set the corn price equal to CHF 0.642 kg^{-1}, the average annual value for the period 1981-2003 in Switzerland (SBV, 1982-2004). We assume a nitrogen price of CHF 1.6 kg^{-1} (LBL, 1993), and a price for irrigation water of CHF 0.06 m^{-3} (Finger and Schmid, 2007). Using these data, the optimal input levels are calculated according to equation (2.9) and represented in Table 2.4.

Table 2.4: Optimal input levels, yield, and maximum net return

Functional Form-Estimation Method	Optimal amount of Nitrogen applied (kg/ha)	Optimal amount of irrigation Water applied (mm)	Optimal yield (kg/ha)	Maximum net return (CHF/ha)
Quadratic-LS	172.8	179.6	9695	5840.32
Square Root-LS	131.3	133.9	9180	5602.82
Mitscherlich-Baule-LS	111.2	61.3	9078	5613.55
Quadratic-RLS	177.4	163.8	9859	5947.68
Square Root-RLS	147.7	108.6	9324	5684.56
Mitscherlich-Baule-IRLS	124.9	116.7	9286	5691.51

Note: LS indicates least squares, RLS reweighted least squares, and IRLS iteratively reweighted least squares estimation.

It shows that all optimal input levels are within the range of the data. With 61.3 mm of irrigation water and 111.2 kg/ha of nitrogen, the lowest input use is recommended by the Mitscherlich-Baule function estimated with LS. This goes along with the lowest yield (9078 kg/ha) and an estimated net revenue of 5613.55 CHF/ha. In contrast, the robust estimated quadratic function shows the highest yield (9859 kg/ha) and nitrogen use (177.4 kg/ha) and the highest profit (5947.68 CHF/ha), while the quadratic LS function implies the highest optimal amount of irrigation water with 179.6 mm. Thus, the quadratic form implies a higher optimal use of nitrogen and irrigation water than all other functions. This confirms with the evidence given by Anderson and Nelson (1975) regarding the overestimation of optimal input amounts by the quadratic form.

Furthermore, the results in Table 2.4 show that the robust versions of production function estimates systematically lead to higher profit maximizing yields and higher profits than their non-robust counterparts. Moreover, for each functional form, the optimal amount of nitrogen fertilizer application increases if robust regression results are taken instead of LS results. And, except for the case of the Mitscherlich-Baule function, robust regression leads to the expected adjustment towards lower use of irrigation water in the profit maximizing situation.

It shows that the range of optimal input levels is much wider for LS than for robust regression. This indicates that differences in optimal input recommendation are not only caused by differences in the analyzed functional forms but also caused by the effect of outliers on LS estimation. All in all, the use of robust estimation narrows the range of optimal input levels across the different functional forms. Thus, the application of robust regression to production function estimation reduces the differences between different functional forms.

Table 2.4 shows furthermore that the selection of the functional form and the selection of the estimation method both affect the result of the economic optimization and allocation problem. This relates to the concept of misspecification costs, which we employ for the final evaluation of production functions and estimation methods. The relative costs of misspecification are defined as the decrease in net return if optimal input levels of an incorrect function are used instead of those of the real underlying production function. With this concept, the potential loss of a misspecification of the production function is minimized. Usually, the focus is on the potential loss due to the wrong functional form. In the following, we also consider the costs of using the improper estimation technique.

Table 2.5 gives the relative costs of misspecification. The nine cells in the upper left-hand corner correspond to the traditional approach where only functional forms estimated with LS are compared. If for instance the quadratic function would be the true underlying form, the use of the square root function induces a cost of misspecification of CHF 93.01. For the Mitscherlich-Baule function, this increases to CHF 297.88. The latter exhibits the highest costs of misspecification, while the square root function is the most appropriate if the misspecification-cost criterion is employed.

The square root function is similar to the quadratic form, but flatter in its surface and comes therefore closer to the plateau approach of the Mitscherlich-Baule specification (Ackello-Ogutu et al., 1985). Optimal input recommendations based on the square root function are correspondingly situated between those of the other two approaches we consider here.

Table 2.5: Relative Costs of Misspecification

When the true function is:	Quadratic-LS	Square Root-LS	Mitscherlich-Baule-LS	Quadratic-RLS	Square Root-RLS	Mitscherlich-Baule-IRLS
	Cost (in CHF/ha) of using optimal input levels based on:					
Quadratic-LS	0	93.01	297.88	4.23	77.85	135.18
Square Root-LS	30.61	0	39.83	32.13	8.41	2.01
Mitscherlich-Baule-LS	113.22	41.38	0	109.97	41.86	27.34
Quadratic-RLS	3.77	104.65	296.39	0	68.59	145.23
Square Root-RLS	7.18	27.08	35.49	8.45	0	23.14
Mitscherlich – Baule-IRLS	57.52	54.08	3.11	51.85	9.86	0

Note: LS indicates least squares, RLS reweighted least squares and IRLS iteratively reweighted least squares estimation.

Table 2.5 further reveals that, in most cases, the use of robust estimation methods results in lower costs of misspecification than the standard LS approach, and that the square root specification performs better under this criterion than the other functional forms. This can be seen when comparing the top left-hand cells with the bottom right-hand ones, as well as from the comparison of the misspecification costs in the different lines of Table 2.5. Only in the cases where the square root specifications are assumed to be the true underlying functions does the quadratic LS estimation show slightly lower costs of misspecification than its RLS counterpart. Furthermore, square root function estimation with LS leads to a marginally lower decrease of the net profit than its robust counterpart if the Mitscherlich-Baule-LS is assumed to be the underlying function. Altogether, this supports the suggestion that the RLS estimation of the square root function is the best approximation of the here analyzed crop response relationship with regard to nitrogen fertilization and irrigation.

2.4 Summary and Conclusions

The improved estimation of production functions might be valuable in practice because crop production functions are widely applied, for instance, to assess agro-environmental policy measures (e.g. Godard et al., 2008) to compare cropping systems (Yadav et al., 2003) or to project future agricultural water demand (e.g. Medellín-Azuara et al., 2008).

In our study, simulated corn yield data for the Swiss Plateau are used for the estimation of crop production functions, with particular consideration of yield response to nitrogen fertilizer and irrigation water application. Three functional forms are considered: the quadratic, the square root, and the Mitscherlich-Baule function. In addition, robust and standard regression methods are used for the estimation.

We found the square root function to be the most appropriate form to represent the data generated with corn yield simulations for Switzerland. Furthermore, exceptional climatic events, such as the summer drought in 2003, are proved to be the major source of misleading results if the least squares criterion is used to estimate production function coefficients. Robust regression methods are recommended instead. The use of robust estimation narrows the range of optimal input levels across the different functional forms. Thus, differences between functional forms are reduced by applying robust regression. This conclusion is further supported by a comparison of the relative costs of misspecification. Using robust instead of least squares regression generally results in lower costs of misspecification. Irrespective of the true underlying functional form, optimal input levels based on robust estimated functions reduce the maximum costs of misspecification compared to the counterparts estimated with least squares regression. Thus, our investigation shows that, besides the functional form, the estimation method is decisive for production function comparisons.

This is even more important for climate change related questions. Climate – and thus crop yield – extreme events are expected to occur more often in the future due to climatic change (e.g. Fuhrer et al., 2006). The properties of robust regression to ensure efficient and reliable coefficient estimation in presence of outliers might thus be particularly valuable for applications and economic assessments related to climate change issues (see e.g. Finger and Schmid, 2008).

Altogether, robust regression is a valuable tool for a wide range of modeling problems that require a proper representation of crop response functions to variable inputs, such as nitrogen fertilizer and irrigation water. Further research should apply other data sets and other robust regression methods, such as MM-estimation, to validate the here presented results. Moreover, in a further step of economic analysis, the observations that are identified as outliers should be re-incorporated in the optimization model. Regression residuals from production function estimation can be used to estimate yield variation with respect to input use. Production and yield variation functions can then be integrated into a utility maximization model that augments the here presented profit maximization approach (e.g. Just and Pope, 1979). Thus, the application of robust regression can improve the estimation of both production and yield variation functions.

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Chapter 3

Modeling Agricultural Production Risk and the Adaptation to Climate Change

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Keywords: biophysical modeling, climate change, crop production functions, crop yields, robust estimation, yield variation

Abstract

An approach that integrates biophysical simulations in an economic model is used to analyze the impact of climate change on Swiss corn and winter wheat production. Adaptation options such as changes in sowing dates, changes in production intensity, and the adoption of irrigation farming are considered in the model. By carrying out sensitivity analysis with different scenarios, we find farmers' adaptation actions and crop yields to be very sensitive to both climate change and output prices. Moreover, our model results show that simple adaptation measures are sufficient to generate higher and less variable crop yields in the future.

3.1 Introduction

In the coming decades Swiss farmers will face changing climatic conditions, which are characterized by elevated carbon dioxide concentrations, reduced summer rainfalls, and elevated temperatures for the Swiss Plateau region (OcCC, 2005). Furthermore, Swiss agriculture will face changing market conditions due to market liberalization. Both input and output prices are expected to decrease in the next decades. To address these concerns, the objective of this paper is to assess impacts of climate change on the production of Swiss corn (Zea mays L.) and winter wheat (Triticum L.) under different price development scenarios.

Previous studies that analyze the effects of climate change (CC) on crop production and crop variability are based either on (crop) simulation or regression models. Crop simulation models simulate and compare crop productivity for different climatic conditions (e.g., Torriani et al., 2007a). Regression models use historical climate and agricultural data to outline potential effects of climate change on crop productivity (e.g., Isik and Devadoss, 2006).

Neither approach is sufficient to analyze all aspects of impacts of CC on crop production (Antle and Capalbo, 2001). If the analysis is restricted to crop physiology, such as in crop simulations, farmers' adaptation actions are not taken into account. But sufficient inference requires consideration of farmers' reactions to changes in climate and economic conditions.

This contrasts with the extrapolation of historical farm-level and aggregated data which take into account farmers' historical reactions to changes in climatic and economic conditions. However, the consideration of adaptation in regression models is limited because new, innovative adaptation measures can not be examined with the extrapolation of historical data. Moreover, historical data are unable to effectively capture future plant-climate interactions, particularly if the crop-weather relationship is restricted to a small number of variables, such as temperature and rainfall. Finally, such models cannot sufficiently integrate expected CO2 fertilization effects on plants due to low variation in historical CO_2 concentrations (Antle and Capalbo, 2001). In order to overcome these drawbacks, we employ a combination of both approaches – simulation of future crop productivity and regression models.

Existing studies show that CC will have particular influence on yield variation (Mearns et al., 1996; Tubiello et al., 2000; Southworth et al., 2002; Fuhrer, 2003; Ciais et al., 2005; Torriani et al., 2007a). The analysis of yield variation is restricted to climatic variables such as shifts in annual means and intra-annual distributions of climatic variables. However, these studies do not adequately address adaptation actions of the farmers. In contrast, our approach considers farmers' adaptation actions to CC and is thus better able to model the impact of CC on yield variation. An empirical example using corn and winter wheat, two of the main crops in Switzerland (Torriani et al., 2007a), is chosen to assess and illustrate the impact of CC on both crop yields and yield variability at the eastern Swiss Plateau.

Our model covers no short-term adaptation actions (i.e., tactical decisions) of farmers, but rather adaptation choices with a longer time horizon, i.e., strategic and structural decisions (cf. Risbey et al., 1999). We consider strategic and structural decisions at the field level consisting of changes in production intensity, changes in sowing dates, and the adoption of irrigation farming. Though crop yields are influenced by various factors, our analysis focuses on the crucial inputs of nitrogen fertilizer and irrigation water. Consequently, this investigation is of particular environmental and economic interest because application of both inputs can lead to the degradation of environmental systems (Institute for European Environmental Policy, 2000; and Khanna et al., 2000). Moreover, nitrogen fertilizer is a major source of climate-relevant agricultural emissions (Hungate et al., 2003).

Our model is based on an integrated assessment approach that combines a biophysical with an economic model. In contrast to other integrated models (e.g., Antle and Capalbo, 2001), farmers' behavior is simulated using nonlinear programming. The model is divided into three major components: data simulation, estimation of model parameters, and economic analysis.

The data simulation module describes the crop yield simulation process which includes the experimental design that enhances yield variability with respect to application of nitrogen fertilizer and irrigation. Additionally, current and simulated future daily weather data are crucial inputs for the simulation process. The data simulation leads to individual data sets for different climatic scenarios and crops that contain yield and input data. These data sets are used to estimate production and yield variation functions. Subsequently, based on these functions, farmers' adaptation choices are analyzed for different climate and price development scenarios using nonlinear programming. Final assessment is based on a comparison of optimal input levels and the corresponding yield levels, yield variation and coefficients of variation for these scenarios of climate change and future price development.

3.2 Crop Yield Simulation

Our analysis is based on yield data generated by the deterministic crop yield simulation model CropSyst (e.g., Stöckle et al., 2003). This is a process-based, multi-crop, multi-year cropping system simulation model. It simulates above- and below-ground processes of a single land block fragment representing a biophysically homogeneous area. These processes are simulated on a daily time step and comprise the soil water budget, soil-plant nitrogen budget, crop phenology, canopy and root growth, biomass production, crop yield, residue production and decomposition, and soil erosion by water.

In CropSyst, processes are simulated in response to weather, soil characteristics, crop characteristics, and management options. The model is therefore suitable for analyzing the impact of environment and management on crop productivity, and has already been tested for a wide range of environmental conditions (e.g., Donatelli et al., 1997; Stöckle et al., 2003). Torriani et al. (2007a) provide a model calibration, tests of yield simulation, and a documentation of critical crop parameters of corn and winter wheat for the eastern Swiss Plateau that are used in our yield simulation.

CropSyst requires daily values of maximum and minimum temperature, solar radiation, and maximum and minimum relative humidity. In CropSyst, phenology is determined by thermal time, i.e., a specific development stage is reached when the required daily accumulation of average air temperature above a base temperature and below a cutoff temperature is reached.

To simulate current climate conditions, we use weather data provided by the Swiss Federal Office of Meteorology and Climate for the years 1981 to 2003 from six meteorological stations distributed over the eastern Swiss Plateau ranging from 06°57' to 08°54' longitude (Finger and Schmid, 2007). Compared to an approach with one single location, incorporating observations from six different weather stations significantly broadens the database. For the atmospheric CO2 concentration input, we use recordings from the years 1981-2003, ranging from 339 ppm to 379 ppm.

Two climate change scenarios are applied to generate crop yields for the coming decades. These climate projections, taken from the Swiss Advisory Board on Climate Change (OcCC, 2005), are based on simulations with two CO_2 emission scenarios, four global climate models, and eight regional climate models. These simulations – with a total of 16 scenario-model combinations on a grid of 50x50 km over the whole European continent – were performed within the scope of the PRUDENCE project (Christensen et al., 2002).

The OcCC climate projections used in this study represent the median of the simulations with the 16 scenario-model combinations for the years 2030 and 2050. Henceforth, these two scenarios are abbreviated as “2030” and “2050”. Based on these scenarios, climate anomalies include seasonal changes of temperature and precipitation for northern Switzerland (Table 3.1).

Table 3.1. Seasonal anomalies of temperature and precipitation

	2030				**2050**			
Description	**Dec. - Feb.**	**March - May**	**June - August**	**Sept. - Nov.**	**Dec. - Feb.**	**March - May**	**June - August**	**Sept. - Nov.**
Temperature	+ 1	+ 0.9	+ 1.4	+ 1.1	+ 1.8	+ 1.8	+ 2.7	+ 2.1
Precipitation	1.04	1.00	0.91	0.97	1.08	0.99	0.83	0.94

Note: This table reports anomalies of temperature in °C (absolute value) and of precipitation in relative values with respect to the climate of the year 1990. Source: OcCC (2005)

From today’s weather data and the anomalies of temperature and precipitation (Table 1), sets of future weather data are developed using the stochastic weather generator LARS-WG (Semenov et al., 1998). Atmospheric CO_2 concentrations vary randomly within the defined range for each climate scenario, with concentrations ranging from 437 ppm to

475 ppm for the 2030 scenario and from 495 ppm to 561 ppm for the 2050 scenario [Intergovernmental Panel on Climate Change (IPCC), 2000].

For each location and scenario, we assume the same uniform soil type as used by Torriani et al. (2007a) to calibrate the CropSyst model for Switzerland. The soil texture is characterized by 38% clay, 36% silt, and 26% sand. CropSyst assesses the hydraulic properties of the soil according to its texture. Soil depth extends to 1.5 m and the soil organic matter content is at 2.6% weight in the top soil layer (5 cm) and 2% in lower soil layers. Soil properties are assumed to be homogeneous over the entire simulated crop area.

The applied management scenarios are uniform on the simulated crop area and include nitrogen (N) fertilization and irrigation. The amount of N applied per year ranges from 0 to 320 kg ha^{-1} for corn and from 0 to 360 kg ha^{-1} for winter wheat. The currently applied amounts of N fertilizer (Walther et al., 2001) are expanded in the simulation in order to cover potential future N fertilization strategies.

For corn (winter wheat), there are three fertilizer applications per year if $N \leq 160$ kg ha^{-1} ($N \leq 180$ kg ha^{-1}) and four fertilizer applications per year if $N > 160$ kg ha^{-1} ($N > 180$ kg ha^{-1}), respectively. For higher N amounts, however, an additional application date is introduced between the second and third dates. In the simulations, fertilizer application dates are defined relative to the sowing date and derived from Dubois et al. (1998) and Walther et al. (2001).

To simulate irrigation, we chose the automatic irrigation option of CropSyst. With this option, irrigation is triggered as soon as soil moisture is lower than a specific user-defined value. The degree of soil moisture is expressed as a value between 0 (permanent wilting point) and 1 (field capacity). When soil moisture falls below the previously defined value, water is added to the soil until field capacity is reached. However, there is an upper limit of irrigation water application of 20 mm per irrigation event. To allow for comparison of the results, the simulated experimental framework is equal for each climate scenario.

For simulations under the current climate we use sowing dates provided by Dubois et al. (1999) and Torriani et al. (2007a). Temperature increase in the climate change scenarios leads to a shift of the annual temperature pattern, and thus to a shift in the period of optimal crop development (Torriani et al., 2007a). Therefore, sowing dates are placed according to the temperature offset of the climate change scenario (Table 3.2). Although sowing dates are placed earlier, CC leads to shorter maturity periods. Consequently, shifts in expected (i.e., sample average) dates of maturity are larger than for sowing dates. For each location and year, one simulation is conducted without application of fertilizer and irrigation. Furthermore, to broaden variability, the amount of fertilizer and the degree of soil moisture that triggers irrigation was varied randomly within the defined range. Depending on the crop and climate scenario, the data sets contain between 527 and 541 observations comprising yield and input data. (Data sets are available from the authors upon request.) A dry matter content of 85% and 90% is assumed for corn and winter wheat yields, respectively.

Table 3.2. Sowing and average maturity dates for the assumed climate scenarios.

		Climate Scenario		
Crop		**Base**	**2030**	**2050**
Corn	Sowing Date	10th May (130)	7th May (127)	4th May (124)
	Expected Day of Maturity	17th September (263)	4th September (250)	28th August (240)
Winter Wheat	Sowing Date	10th October (283)	13th October (286)	16th October (289)
	Expected Day of Maturity	05th August (217)	27th July (208)	18th July (199)

Note: Numbers in brackets are days of year. Source: CropSyst Simulations.

3.3 The Economic Model

The economic analysis is based on maximization of the certainty equivalent (CE), i.e., a certain level of payoff which provides a decision maker with the same utility as a higher but uncertain level of payoff, and is defined as follows:

$$CE = E(\pi) - RP, \tag{3.1}$$

where E is the expectation operator, $E(\pi)$ is the expected quasi-rent π (revenue minus variable costs), and RP is the risk premium, which is the difference between the expected quasi-rent and the certainty equivalent. In our analysis, the risk premium is defined as $RP = \gamma\sigma_{\pi}$, where σ_{π} is the standard deviation of the quasi-rent and γ is the coefficient of absolute risk aversion that indicates risk-averse, risk-neutral, or risk-taking behavior if $\gamma > 0$, $\gamma = 0$, or $\gamma < 0$, respectively.

The variability of quasi-rents can be the result of both stochastic yields and stochastic prices. Input and output prices are assumed to be deterministic in the subsequent analysis. Only crop yields are stochastic, with yield variation $\sigma_Y(X)$. Thus, under assumption of price certainty with a constant output price p, the standard deviation of the quasi-rent can be expressed as (cf. Coyle, 1999):

$$\sigma_\pi = p\sigma_Y(X). \tag{3.2}$$

An indicator function, I, is used to model farmers' adoption of irrigation farming: $I = 1$ for adoption of an irrigation system, and $I = 0$ for crop farming without irrigation. Farmers are assumed to implement an irrigation system if the certainty equivalent minus adoption costs is higher than the certainty equivalent of crop farming without application of irrigation. Specifically, $I = 1$ if and only if $CE(I = 1) - K > CE(I = 0)$, where K denotes the annual costs of adoption (e.g., the rental costs of the irrigation system). The expected quasi-rent is defined as:

$$E(\pi) = pE(Y(X)) - ZX - IK, \tag{3.3}$$

where Z indicates the input prices and Y(X) denotes the functional relationship, i.e., the production function, between output (Y) and inputs (X). Two inputs are considered in the subsequent analysis: nitrogen (N) and irrigation water (W). The decision on adoption of irrigation farming leads to two types of production functions in the model: one with and one without irrigation. This distinction is omitted in this section to ensure clarity.

Yield variation, $\sigma_Y(X)$, is defined here as the absolute difference between observed yields and expected yields: [16]

$$\sigma_Y(X) = \left|Y(X) - E(Y(X)\right|. \tag{3.4}$$

Therefore, the difference between observed and predicted yield for a single observation i corresponds to the absolute residual of the regression analysis ($|e_i|$):

$$\sigma_{Yi}(X_i) = |e_i| = \left|Y_i(X_i) - \hat{Y}_i(X_i)\right|. \tag{3.5}$$

Substitution of equations (3.2) and (3.3) into (3.1) yields the following final optimization problem:

[16] In our analysis, observed yields are yields simulated with CropSyst, and expected yields are observations on the production function.

$$\max_{X,I} CE = pE(Y(X)) - ZX - \gamma\, p\sigma_Y(X) - IK \,. \tag{3.6}$$

The certainty equivalent is maximized subject to the production function constraint Y(X). The first-order conditions for certainty equivalent maximization are presented in a later section.

3.4 Estimation Methodology and Coefficient Estimates

The production function, $Y = f(X)$, is used to estimate the yield responses to nitrogen and irrigation water (cf. Llewelyn and Featherstone, 1997) and is fitted to a square root functional form following Finger and Hediger (2008):

$$Y = \alpha_0 + \alpha_1 N^{0.5} + I\alpha_2 W^{0.5} + \alpha_3 N + I\alpha_4 W + I\alpha_5 (NW)^{0.5} \,, \tag{3.7}$$

where Y denotes corn yield (kg ha^{-1}), N the amount of nitrogen applied (kg ha^{-1}), and W irrigation water applied in mm. The α_i's are parameters that must satisfy the subsequent conditions in order to ensure decreasing marginal productivity of each input factor: $\alpha_1, \alpha_2 > 0$, and $\alpha_3, \alpha_4 < 0$. Further, if $\alpha_5 > 0$, the two input factors are complementary. They are competitive if $\alpha_5 < 0$, while $\alpha_5 = 0$ indicates independence of the two input factors.

The estimation of model parameters is a two-step procedure. The first step is the estimation of production function coefficients (equation 3.7) using robust regression. These estimates are used to calculate robust regression residuals for the entire data set. Subsequently, robust regression residuals are used to estimate yield variation functions in a second step of estimation (equation 3.5). These procedures are described more fully below.

3.4.1 Robust Regression and the Production Function

In this study, robust regression is used to estimate the coefficients of production functions (equation 3.7). This estimation technique was found to increase the accuracy of estimation and to expose the true underlying input-output relationship (Finger and Hediger, 2008).

The main idea of robust regression is to give little weight to outlying observations in order to isolate the true underlying relationship. Outliers are characterized by exceptional yield levels and exceptional input-output relationships, respectively. Hence, they deviate from the relationship described by the majority of the data. The identification of the true relationship and of outliers, respectively, is a nontrivial challenge, particularly if the situation exceeds the simple regression case. We use the reweighted least squares (RLS) regression for the robust estimation. RLS is a weighted least squares regression, which is based on an analysis of least trimmed squares (LTS) regression residuals that assigns zero weights to observations identified as outliers (see Rousseeuw and Leroy, 1987, for details). An observation is identified as an outlier if the standardized LTS residual exceeds the cutoff value of 2.5 (Hubert et al., 2004).

The estimation of coefficients and related residuals with ordinary least Ssquares (OLS) regression can be inefficient if extreme yield events (i.e., outliers) are analyzed. One outlier can be sufficient to move the coefficient estimates arbitrarily far away from the actual underlying values (Rousseeuw and Leroy, 1987; Hubert et al., 2004). Thus, any analyses based on regression residuals derived by OLS estimation are inefficient and can produce misleading results.

In contrast, robust regression such as RLS enables efficient estimation in the presence of outliers. Additionally, to correct for heteroskedasticity, feasible generalized least squares (FGLS) regression is applied (see Johnston and DiNardo, 1997, for details). Hence, weights are generated with respect to both, outliers and heteroscedasticity in the final estimation of production functions. The estimation is conducted with the ROBUSTREG and MODEL procedures of the SAS statistical package (SAS Institute, Inc., 2004).

3.4.2 Coefficient Estimates for the Production Functions

Coefficient estimates of the corn and winter wheat production functions for the assumed climate scenarios are presented in Table 3.3. It shows that coefficient estimates have the correct (expected) sign. The intercept, i.e., the yield where neither nitrogen nor irrigation is applied, shows an increase from the base scenario to the 2050 scenario for both crops. This is because of more favorable climatic conditions for crop growth. In particular, an increased CO_2 concentration leads to higher yield levels (Fuhrer, 2003). Further, these yield increases are the result of applied shifts in sowing days, as this is a powerful adaptation option to avoid negative effects of climate change (cf. Southworth et al., 2002, and Torriani et al., 2007a).

The analysis of yields where neither irrigation nor nitrogen fertilization takes place is purely hypothetical. Both winter wheat and corn farm management without any input use are nonexistent in Switzerland. Therefore, conclusions about the impact of climate change on yield levels can be drawn if and only if optimal input levels and corresponding optimal yield levels are calculated (such as given in a subsequent section below). The coefficient estimates presented here are used as input in the economic model.

Table 3.3 shows a constant increase of the interaction parameter $(NW)^{0.5}$ from the base to the 2050 scenario for corn. Thus, independency of nitrogen fertilizer and irrigation water in the base and 2030 scenarios shifts to significant complementary interaction in the 2050 scenario. The interaction is important, as nitrogen is taken up in a water solution. In the first two scenarios, nitrogen uptake is sufficiently ensured by precipitation. In the latter scenario, which is characterized by lower amounts of summer rainfall (Table 3.1), optimal nitrogen uptake in corn production is only ensured if irrigation takes place. Therefore, climate change is expected to increase the application of nitrogen fertilizer in the presence of irrigation, but to decrease nitrogen application if no irrigation is available. However, as observed in Table 3.3, this is not the case for winter wheat. The interaction parameter $(NW)^{0.5}$ is not affected by CC. It remains low and is not significantly different from zero for all climate scenarios. Winter wheat is less vulnerable to increased temperature and decreased summer rainfall than spring sown crops such as corn. This finding is in agreement with the results reported by Torriani et al. (2007a) who already pointed out that irrigation will become more important for spring than for winter crops in Switzerland.

Table 3.3. Coefficient Estimates: Production Function for Corn and Winter Wheat (equation 3.7)

Coefficient	Climate scenario Base	 2030	 2050
		Corn	
Intercept	6601.92 (162.13)**	6972.65 (180.68)**	7053.14 (165.17)**
$N^{0.5}$	313.09 (16.34)**	347.61 (19.79)**	309.87 (16.36)**
$W^{0.5}$	67.14 (4.17)**	59.65 (4.69)**	71.59 (5.50)**
N	-10.54 (8.15)**	-11.00 (9.38)**	-9.59 (7.60)**
W	-2.50 (2.17)*	-0.93 (1.09)	-1.02 (1.19)
$(NW)^{0.5}$	0.36 (0.45)	1.04 (1.55)	3.52 (4.92)**
Adjusted R^2	0.73	0.84	0.84
		Winter Wheat	
Intercept	4582.36 (67.37)**	4894.40 (80.81)**	5142.07 (81.35)**
$N^{0.5}$	161.23 (9.34)**	178.41 (11.93)**	151.34 (9.64)**
$W^{0.5}$	25.48 (1.18)	70.17 (3.73)**	68.30 (3.38)**
N	-5.24 (5.43)**	-5.97 (7.16)**	-5.18 (5.90)**
W	-0.86 (0.56)	-2.94 (2.19)*	-3.47 (2.36)*
$(NW)^{0.5}$	0.51 (0.59)	-0.36 (0.48)	0.54 (0.67)
Adjusted R^2	0.39	0.47	0.37

Note: Statistics in parentheses are t statistics. Double and triple asterisks (*) denote statistical significance at the 5% and 1% level, respectively.

3.4.3 Yield Variation Function

Observations which are identified as outliers are not taken into account for the final estimation of production function coefficients. Yet, these observations are of particular interest for the estimation of yield variation because they increase yield variation. Therefore, residuals are calculated for the entire data set, including the observations identified as outliers. The inclusion of outliers in the remaining analysis is possible if and only if no typing, copying, or measuring errors other than exceptional climatic events are the source of the identified outliers, as proved by Finger and Hediger (2008) using the same data sets.

Yield variance is estimated using regression residuals (equation 3.5) and is determined, among other factors such as weather and soil, by input use. This relationship is modeled using a square root function for corn. Irrigation water (*W*) is only an element of yield variation functions for irrigation farming ($I = 1$):

$$\sigma_Y(X) = \beta_0 + I\beta_1 W^{0.5} + \beta_2 N^{0.5}. \tag{3.8}$$

Shifts in the intercept, β_0, capture effects of changes in weather conditions on yield variation across different climate scenarios; β_1 and β_2 quantify the influence of irrigation and nitrogen application on yield variation. An input is risk decreasing if $\beta_i < 0$, and risk increasing if $\beta_i > 0$.

For winter wheat, a quadratic specification was found to be most appropriate:

$$\sigma_Y(X) = \beta_0 + I\beta_1 W + \beta_2 N^2 + \beta_3 N \tag{3.9}$$

Interpretation of coefficients β_0 and β_1 remains the same as in equation 3.8. The influence of nitrogen on yield variation was found to have a quadratic shape for winter wheat, first decreasing, then increasing yield variation [coefficients β_2 and β_3 in equation (3.9)].

The yield variation functions are estimated using the MODEL procedure of the SAS statistical package and FGLS regression to correct for heteroskedasticity. In contrast to other studies that focus on heteroskedasticity correction (Just and Pope, 1979) and take simultaneous equation biases into account (Isik and Khanna, 2003), our estimation approach is oriented toward efficient estimation in the presence of extreme events. Given that such events are more likely to occur with changing climate (e.g., Fuhrer et al., 2006), this property is of particular interest.

3.4.4 Coefficient Estimates for the Yield Variation Functions

Table 3.4 reports final coefficient estimates for the yield variation functions for corn and winter wheat [equations (3.8) and (3.9)]. For both crops, the intercept coefficient β_0 (i.e., yield variation solely determined by weather and soil conditions) decreases from the base to the 2030 scenario and increases in the 2050 scenario. Thus, if neither irrigation nor nitrogen fertilizer application were to take place, yield variation would increase from the 2030 to the 2050 scenario.

For corn, irrigation, ceteris paribus, causes a decrease ($\beta_2 < 0$) and nitrogen fertilizer causes an increase ($\beta_1 > 0$) in yield variation. The propensity of irrigation to reduce corn yield variation ($|\beta_2|$) continuously increases along our climate change scenarios. Higher temperature and lower summer rainfall cause irrigation to be a more risk-decreasing activity than it is currently.

Table 3.4. Coefficient Estimates: Yield Variation Function for Corn and Winter Wheat.

Coefficient	Climate scenario		
	Base	**2030**	**2050**
		Corn (equation 3.8)	
Intercept	409.03 (14.78)**	381.75 (18.33)**	468.51 (19.52)**
$N^{1/2}$	38.98 (10.78)**	39.21 (11.82)**	39.82 (11.26)**
$W^{1/2}$	-8.13 (2.41)*	-12.75 (5.32)**	-20.29 (8.19)**
adj. R^2	0.19	0.24	0.27
		Winter Wheat (equation 3.9)	
Intercept	789.23 (23.11)**	680.50 (22.21)**	728.55 (23.60)**
W	-0.50 (1.63)	-0.41 (1.50)	-0.45 (1.62)
N^2	0.004 (2.37)*	0.006 (3.97)**	0.009 (5.75)**
N	-2.19 (3.85)**	-2.51 (4.97)**	-3.38 (6.69)**
adj. R^2	0.07	0.05	0.08

Note: Statistics in parentheses are t statistics. Double and triple asterisks (*) denote statistical significance at the 5% and 1% level, respectively.

In contrast, the coefficient β_1, the propensity of nitrogen fertilizer to increase yield variation, is nearly constant under different climate conditions. We expect no impact of climate change on the relationship of yield variation and nitrogen for corn production.

For winter wheat, nitrogen first causes a decrease, then an increase in yield variation. Irrigation causes a decrease of the latter. In contrast to the results for corn, the relationship between input use and yield variation is not affected by CC for both nitrogen and irrigation inputs. However, conclusions about the impact of climate change on the yield variation can be drawn if and only if optimal input levels and the according yield variations are calculated (such as presented in the section below).

3.5 Optimal Input Use, Yield, Yield Variation, and Adoption Rates

Predictions about the influence of climate change on input use, yield levels, and yield variability require modeling of farmers' behavior. To this end, the certainty equivalent is maximized as described earlier. Derived optimal input levels provide the highest certainty equivalents per hectare. Input prices (*Z*) are restricted to variable costs. Thus, considering nitrogen fertilizer (*N)* and irrigation (*W*) only, *ZX* is defined as the variable nitrogen costs (nitrogen applied x nitrogen price) plus the variable irrigation costs (irrigation water applied x irrigation water price). Other costs are assumed constant and thus irrelevant for the certainty-equivalent-maximizing input combination. The first-order conditions for optimal input use [equation (3.6)], are expressed as follows:

$$\partial f(x_i^*)/\partial x_i - z_i / p - \gamma \cdot \partial \sigma_Y(X)/\partial x_i = 0 \qquad \forall i, \tag{3.10}$$

where, z_i denotes the price and x_i^* the optimal level of input *i*. For $\gamma \neq 0$, the respective propensity of inputs to increase and decrease yield variation, $\partial \sigma_Y(X)/\partial x_i$, affects optimal input use. The optimal level of factor use for an input that increases yield variation is smaller for a risk-averse than for a risk-neutral agent, and vice versa. Equation (3.10) is solved for both irrigation and non-irrigation farming independently.

3.5.1 Price Development Scenarios

Current Swiss agricultural output and input prices are much higher than in other European countries. Due to market liberalization, Swiss agriculture will face diminishing output-input price ratios in crop production down to levels of, for instance, the European Union (EU). The differences between current (referring to 2006) Swiss and EU prices are much smaller for inputs such as nitrogen fertilizer than for outputs such as corn and wheat. Because detailed price forecasts for the periods of interest are impossible to calculate, and in order to show the sensitivity of adaptation processes to both climate change and price development, we assume three price development scenarios for 2030 and 2050 – ranging from current EU prices (P_{EU}) to 1.5 x P_{EU} and 2 x P_{EU}.

Price assumptions are presented in Table 3.5 and are documented in Finger and Schmid (2007). Current Swiss prices are applied for the base scenario. Moreover, our numerical analysis is restricted to one example of constant (i.e., independent from the level of certainty equivalents) absolute risk aversion with $\gamma = 0.5$.

Table 3.5. Price Development Scenarios (in CHF)

Price Scenario	Corn kg^{-1}	Wheat kg^{-1}	Nitrogen kg^{-1}	Irrigation (mm per ha)
Current	0.396	0.57	1.33	0.6
P_{EU}	0.185	0.182	0.91	0.6
1.5 x P_{EU}	0.2775	0.273	0.91	0.6
2 x P_{EU}	0.37	0.364	0.91	0.6

3.5.2 Model Results

First-order conditions [equation (3.10)] are solved for both crops taking into account the three price development scenarios (Table 3.5). For the sake of brevity, not all results are presented in detail. For one price development scenario (P_{EU}), Table 3.6 presents optimal factor inputs, certainty equivalents, optimal yield, and optimal yield variation for corn and winter wheat. Results are reported for both irrigation and non-irrigation farming. Differences in input levels, certainty equivalents, yields, and yield variation between irrigation and non-irrigation farming are also provided. All results are within the range of the data.

As shown by Table 3.6, the assumed combination of price development and climate change scenarios has only small effects on optimal use of nitrogen fertilizer for corn. In contrast, the optimal amount of applied irrigation water more than doubles from the base and the 2030 scenario to the 2050 scenarios. Due to reduced output prices, future levels of certainty equivalents are lower than currently. Yield levels increase by up to 20% from the base to the 2050 scenario for irrigation farming ($I = 1$). In contrast, optimal levels of corn yields decline from the 2030 to the 2050 scenario for non-irrigation farming. Corn yield variation decreases from the base to the 2050 scenario for irrigation farming but increases for non-irrigation farming.

For winter wheat, optimal amounts of nitrogen and irrigation water are smaller for the future scenarios compared with the base scenario mainly because of the reduced output-input price ratio. Both climate change and irrigation farming have only small impacts on yield variation of winter wheat. Therefore, differences between irrigation and non-irrigation farming are much smaller for winter wheat than for corn. In particular, the yield gap between irrigation and non-irrigation farming – i.e., the expected yield increase due to application of irrigation farming – is at maximum 307 kg ha^{-1} for winter wheat but 1,596 kg ha^{-1} for corn (2050 scenario, Table 3.6).

Adoption of irrigation farming is triggered by differences of certainty equivalents between irrigation and non-irrigation farming in our model. For both crops, differences of certainty equivalents, $CE(I=1)-CE(I=0)$, decrease from the base to the 2030 scenario due to the decline of output prices (Table 3.6). For corn, this difference increases considerably in the 2050 scenario. Even though the output price is lower, CC leads to a higher profitability of irrigation in corn farming. This contrasts with the results for winter wheat, where the profitability of irrigation remains low in the 2050 scenario.

Results of the remaining price development scenarios can be summarized as follows. Higher output prices cause higher input use and thus higher yield levels and higher levels of certainty equivalents. Furthermore, this leads to larger certainty equivalent differences between irrigation and non-irrigation farming for both crops. Thus, an increase of output prices, ceteris paribus, causes higher profitability of irrigation farming.

Table 3.6. Optimal Input Levels, Certainty Equivalents, Yields and Yield Variation for Corn and Winter Wheat.

Climate Scenario	Nitrogen (kg ha^{-1})	Irrigation Water (mm)	Certainty Equivalents (per ha)	Yield (kg ha^{-1})	Yield Variation (kg ha^{-1})
			Corn		
I=1 (irrigation)					
Base	114.10	87.48	3286.20	9189	749
2030	112.48	85.20	1632.79	9995	680
2050	137.93	208.49	1685.66	10788	643
I=0 (non-irrigation)					
Base	111.50	0	3147.22	8732	821
2030	106.16	0	1567.24	9387	786
2050	99.84	0	1529.50	9192	866
Diff. between I=1 and I=0					
Base	2.60	87.48	138.98	457	-72
2030	6.32	85.2	65.55	608	-106
2050	38.09	208.49	156.16	1596	-223
			Winter Wheat		
I=1 (irrigation)					
Base	138.59	90.01	3019.59	5976	520
2030	75.03	30.87	1007.01	6274	515
2050	71.33	30.92	1023.44	6348	519
I=0 (non-irrigation)					
Base	131.72	0	2934.92	5743	573
2030	76.58	0	973.16	5999	525
2050	68.93	0	986.67	6041	538
Diff. between I=1 and I=0					
Base	6.87	90.01	84.67	233	-53
2030	-1.55	30.87	33.85	275	-10
2050	2.40	30.92	36.77	307	-19

Note: The price development scenario reported here is P_{EU}.

3.5.3 Adoption of Irrigation Farming

Farmers are assumed to adopt irrigation farming $(I = 1)$ if and only if $CE(I = 1) - K > CE(I = 0)$, where K denotes the annual adoption costs per hectare (e.g., for renting of equipment). Adoption costs are modeled stochastically to reflect heterogeneous adoption costs for farmers due, for example, to differences in farm size, access to irrigation water and infrastructure endowments (Kulshreshtha and Brown, 1993). One hundred thousand draws are made from a normal distribution $(\mu = 200, \sigma = 40)$. This results in simulated costs, expressed in certainty equivalents, which range from 20 to 385 units with an inter-quartile range between 173 and 226. While this distribution of costs is not representative, it avoids corner solutions compared with a single value for adoption costs. Hence, this approach is more suitable to highlight the sensitivity of the model. Comparison between the scenarios is ensured by applying identical distributions of costs for each scenario. Every simulated observation adopts irrigation farming if the certainty equivalent difference between irrigation and non-irrigation farming (see Table 3.6) is larger than the simulated costs.

Simulated adoption rates are smaller than 1% for winter wheat. Irrespective of the price development scenarios, the assumed CC scenarios do not lead to adoption of irrigation farming in winter wheat production. This is because shifts in maturity stages avoid heat stress in summer (Table 3.2), and reductions of relevant spring rainfall are small in the assumed climate change scenarios (Table 3.1). These findings are consistent with the results of Torriani et al. (2007a) who found only marginal benefits of irrigation in winter wheat farming on the eastern Swiss Plateau for current and future climatic conditions.

In contrast, the adoption rate in the base scenario for corn is 6.5 %. As shown in Table 3.7, higher prices generally lead to higher adoption rates. As a consequence, all farmers switch to irrigation farming in 2050 for the 1.5 x P_{EU} and 2 x P_{EU} price development scenarios in our model. Assuming P_{EU}, however, the highest adoption rate is 13.75% for the 2050 scenario. Specifically, even in 2050, the adoption of irrigation farming will be relatively small if Swiss farmers' face current EU prices.

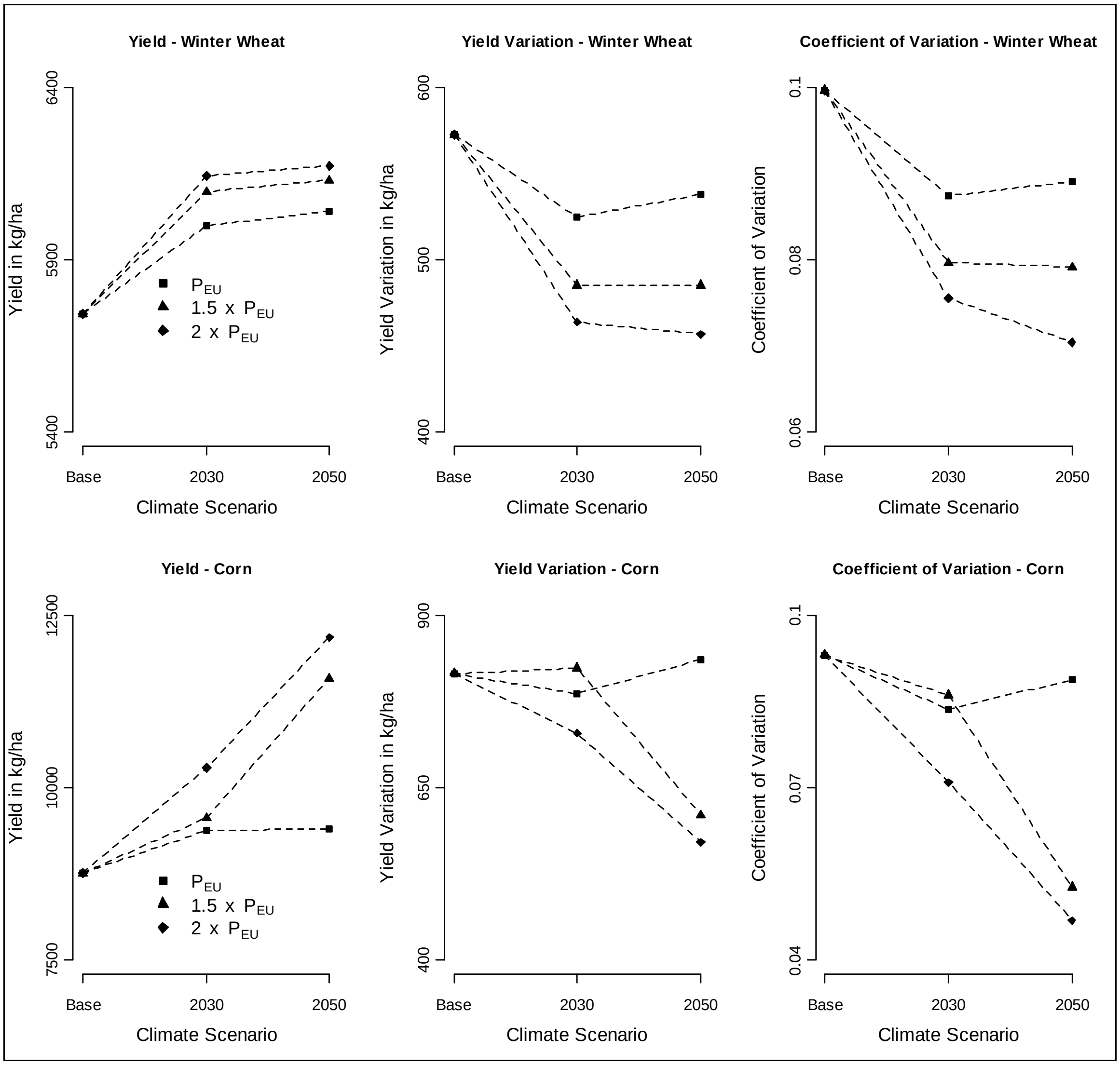
Table 3.7. Adoption Rates of Irrigation Farming for Corn (in %)

Climate Scenario	**Price Scenario**		
	P_{EU}	**1.5 x P_{EU}**	**2 x P_{EU}**
Base	6.45	6.45	6.45
2030	0.05	5.95	74.52
2050	13.75	100.00	100.00

To obtain final results, the adoption rates are combined with the results for input use, yield level, yield variation, and certainty equivalents. For instance, the final result for yields (Y^*) is calculated as follows: $Y^* = adoption\ rate \times Y^*(I=1) + (1 - adoption\ rate) \times Y^*(I=0)$. For farmers who adopt irrigation farming, certainty equivalents are reduced by the average adoption costs revealed in the respective simulated sample.

Final model results for yield levels, yield variation, and coefficients of variation are illustrated in Figure 3.1. It shows increasing yields and decreasing yield variation for corn and winter wheat production in the future. Although corn yield variation increases for two scenarios (P_{EU} in 2050, and 1.5 x P_{EU} in 2030), the coefficients of variation (i.e., the ratio of yield variation and yield level) for all price development scenarios are unambiguously smaller than in the base scenario. Moreover, Figure 3.1 shows that higher output prices lead to smaller coefficients of variation for both corn and winter wheat. Because positive effects of CC on yield production cannot offset reduced output prices, the future certainty equivalents decrease for all but the 2 x P_{EU} price development scenario for corn (not shown).

Figure 3.1. Final Model Estimates for Yield, Yield Variation and Coefficient of Variation for Corn and Winter Wheat.



3.6 Discussion and Conclusions

Approaches of earlier studies analyzing the impact of climate change on crop production were not able to incorporate both future climate-plant interactions and adaptation measures simultaneously. To overcome this drawback, we use a modeling approach that combines predicted climate-plant relationships (crop simulation modeling) and an economic model that focuses on strategic adaptation.

We find beneficial effects of climate change if adaptation measures such as changes in sowing dates, changes in production intensity, and implementation of irrigation systems are taken into account. For the time horizon considered in this analysis (2030–2050), we expect Swiss corn and winter wheat yields to increase above current levels.

Using a regression modeling approach, Flückiger and Rieder (1997) projected decreasing corn and increasing winter wheat yields in Switzerland. Their projections for winter wheat are consistent with the findings of our analysis because the adaptation options considered here do not significantly change the impact of climate change on winter wheat production. The contrasting findings for corn yield projections are due to the adaptation measures that are taken into account in our analysis but are not considered by Flückiger and Rieder.

Yield variation in Switzerland is projected to increase for corn and to decrease for winter wheat according to the analysis of Torriani et al. (2007a), which is restricted to potential crop yields and employs a crop simulation approach. The latter result supports our findings. However, the increase of corn yield variation is inconsistent with our results because economic incentives for farmers' adaptation in general, and production intensity adjustment in particular, are not taken into account by Torriani et al.

Our results further indicate that adaptation actions, and thus crop yield development, are determined by both future climate and future crop prices. This finding is particularly important for Switzerland because changes in crop prices due to market liberalization are expected to be large.

Our approach of modeling impacts of climate change on crop production and production risk is valuable for future research because it enables the simultaneous analysis of climate change and price scenarios. In particular, adaptation measures at the farm level (e.g., changes in crop rotation patterns) should be further integrated into such a modeling approach.

In order to validate our results, further soil types and additional climate change, price development and risk-aversion scenarios should be considered. Additional climate change scenarios should emphasize the probability of future extreme climatic events such as droughts. The procedure proposed here for estimation of model parameters is suitable for the incorporation of such extreme climatic events. Using robust regression for production function estimation ensures efficient estimation of model parameters in the presence of outliers (e.g., observations caused by extreme climatic events).

Our case study shows that simple adaptation measures at the field level – such as changes in sowing dates, changes in production intensity, and adoption of irrigation farming – are sufficient to generate positive effects of climate change for corn and winter wheat production at the eastern Swiss Plateau. Taking into account that further adaptation measures such as breeding of new varieties and financial instruments such as weather derivates were found to be valuable adaptation strategies for Swiss crop production (Torriani et al., 2007a, 2008), the latter is expected to benefit from climate change.

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Chapter 4

The Impact of Climate Change on the Profitability of Site Specific Technologies

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Abstract

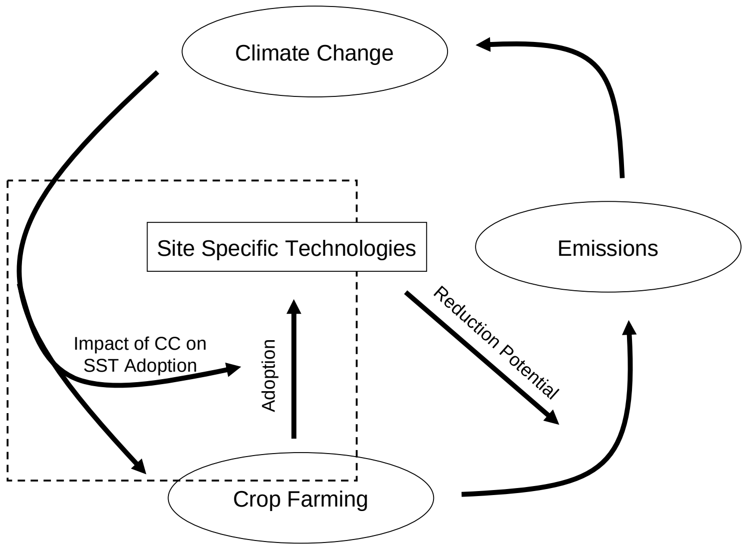
Site Specific Technologies (SST) can reduce environmental pollution caused by common agricultural practice. Using a case study for corn yields, we investigate the impact of climate change (CC) on profitability of SSTs. We find CC to increase spatial variability of soils with respect to optimal input application and yield variability. This leads, ceteris paribus, to higher incentives for SST adoption in the future.

4.1 Introduction

The relationship between agriculture and the environment is a major issue in agricultural research. It shows that common agricultural practice causes environmental pollution and leads to unsustainable use of resources such as soil and water (OECD, 2001). It is of particular social but also economic interest to foster pollution reduction and sustainable use of resources by agriculture. Site Specific Technologies (SSTs) are potential instruments to reach such goals. In contrast to conventional management practice, where inputs are applied uniformly across the field, management that employs SSTs is characterized by input application taking spatial variability across the field into account. Various studies show that SSTs lead to lower application rates of harmful inputs, reduce residues of inputs in soil and reduce emissions caused by fertilizer application (Anselin et al., 2004; Isik and Khanna, 2002; 2003; Khanna et al., 2000; Pampolino et al., 2007; Roblin and Barrow, 2000). Our analysis is restricted to the crucial agricultural inputs nitrogen fertilizer and irrigation water because application of both can lead to the degradation of environmental systems (IEEP, 2000; Khanna et al., 2000). Nitrogen fertilizer is furthermore a major source of climate relevant agricultural emissions (Hungate et al., 2003).

Projected changes in climatic conditions will cause changes in the productivity of crops and crop yield variability in the next decades. In particular soil characteristics determine the impact of climate change (CC) on crop yields (e.g. Eitzinger et al., 2003; Wassenaar et al., 1999). Thererfore, CC is assumed to increase spatial variability of soils with respect to yield potentials, input use and yield variability, respectively. The latter are important for the profitability of SSTs (Isik and Khanna, 2003). Thus, CC is assumed to affect adoption of SSTs. Using a case study, this paper focuses on the relationship between CC and the incentive of crop farmers to use SSTs (shown in dashed box of Figure 4.1).

Figure 4.1: The relationship of crop farming, climate change and SSTs.



Source: own illustration

We use simulated corn (*Zea Mays L.*) yields, which are particularly sensitive to field level variations of the soil properties (Tittonell et al., 2006), at the eastern Swiss Plateau considering a base scenario of current climate and a CC scenario for the year 2050.

The remainder of this paper is organized as follows. The economic model that estimates profitability of site specific management is presented in Section 4.3. Section 4.4 describes briefly the yield simulation process and the CC scenario. In Section 4.5, empirical methods and estimation results are presented. Model results and expected differences between conventional and site specific management are shown in Section 4.6. Finally, the impact of CC on SST adoption is discussed in the concluding section 4.7.

4.2 The Model

Our analysis is based on maximization of expected utility[17], $E(U(\pi,\sigma))$, with $E(U)_{\pi} > 0$ and $E(U)_{\sigma} < 0$. Where E is the expectation operator, π are quasi-rents (revenue minus variable costs) and σ is the standard deviation of quasi-rents. Two management technologies are considered in this model: site specific and conventional management. In a static analysis, the utility maximization problem with respect to management technology choice is defined as follows (Isik and Khanna, 2003):

(4.1) $$\max_{I} E(U(\pi^C + I(\pi^S - \pi^C - K), \sigma^C + I(\sigma^S - \sigma^C)))$$

Where π^C and π^S are the quasi-rents for conventional and site specific management, respectively. I is an indicator function, i.e. $I = 1$ for SST adoption and $I = 0$ if conventional management is maintained. K denotes the costs of adoption, i.e. variable costs for hiring technology and experts (Khanna et al., 2000). σ^C and σ^S are the standard deviations of quasi-rents for conventional and site specific management, respectively. Therefore, site specific management is adopted if:

(4.2) $$E(U(\pi^S - K, \sigma^S)) > E(U(\pi^C, \sigma^C)).$$

Farmers are assumed to adopt site specific management if expected utility exceeds utility of conventional management practice and adoption costs. In our analysis, prices are assumed to be deterministic. Thus, the standard deviation of quasi-rents (i.e. the production risk) simplifies to $\sigma(\pi) = p\ \sigma^Y(X)$. Yield, with standard deviation $\sigma^Y(X)$, is the only stochastic element of quasi-rents. Hence, the optimization problem with respect to input use is defined as follows:

(4.3) $$\max_{X,Y} E(U(\pi)) = pE(Y(X)) - ZX - \gamma\ p\ \sigma^Y(X) \quad .$$

p and Z are output and input prices, respectively. Moreover, $Y(X)$ denotes the production function, i.e. the input (X) - output (Y) relationship. Expected utility is maximized subject to the production function constraint. The coefficient of absolute risk aversion, γ,

[17] Subscripts denote derivatives.

indicates risk averse, risk neutral and risk taking behavior if $\gamma > 0$, $\gamma = 0$, and $\gamma < 0$, respectively. $\sigma^{Y}(X)$, the yield variation, is determined by weather and soil conditions, and input use. Input *i* is risk decreasing if $\sigma^{Y}_{x_i} < 0$ and risk increasing if $\sigma^{Y}_{x_i} > 0$.

The first order conditions of eqn. (4.3) are:

(4.4) $\partial E(U(x^{i*}) / \partial x^{i} = \partial E(\pi(x^{i*})) / \partial x^{i} - \partial \gamma\ p\ \ \sigma^{y}(x^{i*}) / \partial x^{i} = 0 \quad \forall i$

These first order conditions are equivalent to:

(4.5) $\partial f(x^{i*}) / \partial x^{i} - z^{i} / p - \gamma \sigma^{y}_{x_i} = 0 \quad \forall i$,

where, x^{i*} is the optimal factor level and z^{i} is the price of input *i*. This tangency condition equals profit maximization if $\gamma = 0$. However, the optimal level of input use is smaller for an input that increases yield variation, if a risk averse instead of a risk neutral farmer is considered, and vice versa.

In order to reflect heterogeneous soil conditions, the assumed field with land size *M* is divided into *T* sites of equal size[18]. Soil characteristics are homogeneous within each site but heterogeneous across sites. In our analysis, soil characteristics vary with respect to content of organic matter and soil fertility. Other soil characteristics, such as the soil texture, are assumed to be homogeneous across sites. Details on soil characteristics that are assumed in our analysis are given in the subsequent section 4.4. In order to model sites at the field, we draw (1000 draws) a site from a binomial distribution of two soils that are abbreviated as *S1* and *S2* in the following. In this distribution, probability to draw *S1* (*p(S1)*) and probability to draw *S2* (*p(S2)*) is 0.4 and 0.6, respectively.

For every drawn soil composition (i.e. ratio of *S1* and *S2*), four expected utilities are calculated: for site specific management and for conventional management with three different levels of information. For site specific management the soil type of each site is known and utility is maximized for each site, $j = 1,...,T$. Therefore, field level expected utility for site specific management, $E(U(\pi^{S}))$, is defined as follows:

---

[18] $M = \sum_{j=1}^{T} M^{j}$

(4.6) $$E\left(U(\pi^S)\right) = \sum_{j=1}^{T} M^j E\left(U(\pi^j)\right) = \sum_{j=1}^{T} M^j \left(pE(Y(X^{j*})) - ZX^{j*} - \gamma\, p\ \sigma^Y(X^{j*})\right).$$

In contrast, soil types of sites are not known if conventional management practice is assumed. We assume three different levels of farmers' soil information: a) zero information: every input combination between $X^*(S1)$ and $X^*(S2)$ has the same probability to be applied, i.e. drawn from a uniform distribution; b) ratio of soil components (*S1* and *S2*) is known: X^C is equal to $0.4X^*(S1) + 0.6X^*(S2)$; c) rough information of soils: in order simulate an information situation in between the extremes (a, b), input combinations are drawn from a non-uniform discrete distribution[19]. Simulations are conducted with @Risk (Winston, 1996).

Based on their soil information, farmers maximize expected utility $E\left(U^C\left(\pi^C(X^C), \sigma^C(X^C)\right)\right)$. Input application for conventional management, X^C, depends on the soil information scenario (a-c). Field level expected utility for conventional management, $E\left(U\left(\pi^C\right)\right)$, is defined as follows:

(4.7) $$E\left(U(\pi^C)\right) = pE(Y(X^C)) - ZX^C - \gamma\, p\ \sigma^Y(X^C)\,.$$

The goal of this paper is to analyze the impact of CC on the profitability of SST adoption. Therefore, the utility maximization problem with respect to technology choice (eqn. 4.1) is reduced to the expected utility difference between site specific and conventional management (eqn. 4.8). This expected utility difference is calculated twice, for the base and the CC scenario.

(4.8) $$\Delta E\left(U(S,C)\right) = E\left(U(\pi^S, \sigma^S)\right) - E\left(U(\pi^C, \sigma^C)\right)$$

4.3 Data

Our analysis is based on corn yield data generated with the deterministic crop yield simulation model CropSyst (Stöckle et al., 2003). CropSyst parameterization for Swiss corn follows Torriani et al. (2007a). Yield simulations are provided by the Agroscope

[19] Probability (p) to draw $X_i^*(S1)$ =0.05, $p(0.8X_i^*(S1) + 0.2X_i^*(S2))$=0.1, $p(0.6X_i^*(S1) + 0.4X_i^*(S2))$=0.2, $p(0.4X_i^*(S1) + 0.6X_i^*(S2))$=0.3, $p(0.2X_i^*(S1) + 0.8X_i^*(S2))$=0.25, $p(X_i^*(S2))$ =0.1

Reckenholz-Tänikon Research Station ART in Zurich. Apart from agricultural inputs and CO_2 concentrations, CropSyst is particularly driven by daily values of maximum and minimum temperature, solar radiation, and maximum and minimum relative humidity. Required weather data are provided by the Swiss Federal Office of Meteorology and Climate for six different locations on the eastern Swiss Plateau (Finger and Schmid, 2007). We use recordings for the years 1981 to 2003 which represent the base climate scenario. Assumed seasonal changes in temperature and precipitation for the CC scenario (abbreviated in the following as 2050) are presented in Table 4.1.

Table 4.1: Seasonal anomalies of temperature [°C] (absolute value) and precipitation [-] (relative value) with respect to the climate of the year 1990.

Climate variable	**2050**			
	DJF	**MAM**	**JJA**	**SON**
Temperature [°C]	+ 1.8	+ 1.8	+ 2.7	+ 2.1
Precipitation [-]	1.08	0.99	0.83	0.94

DJF: December-February; MAM: March-May; JJA: June-August; SON: September-November.

Source: OcCC (2005)

Based on climate anomalies, daily weather data for the 2050 scenario are generated with the stochastic weather generator LARS-WG (Semenov et al., 1998). Furthermore, CO_2 concentrations are randomly allocated to the observations. These concentrations range from 339ppm to 379ppm for the base and from 495ppm to 561ppm for the 2050 scenario (IPCC, 2000), respectively. The applied soil texture for both soil types (*S1* and *S2*) is characterized by a fraction of 26% sand, 38 % clay and 36% silt. Soil depth amounts to 1.5 m. For soil 1 (*S1*), the soil organic matter content is constant at 2.6%. For soil 2 (*S2*), the latter is 2.6% in the top soil layer (5 cm) and 2.0% in lower soil layers. Due to higher content of organic matter in *S1* than in *S2*, higher amounts of nitrogen are mineralized from organic matter (Table 2). Thus, soil fertility in *S1* is higher than for *S2*.

Table 4.2: Average amount of nitrogen mineralized from organic matter for Soil 1 and Soil 2.

	Average amount of nitrogen mineralized from organic matter in kg/ha	
Climate Scenario	**Soil 1 (*S1*)**	**Soil 2 (*S2*)**
Base	115.65	88.54
2050	115.22	91.09

Source: CropSyst simulations

Sowing of corn is placed six days earlier in the 2050 than in the base scenario. Earlier sowing in corn farming is a powerful adaptation option to avoid negative effects due higher temperatures and reduced precipitation in the assumed CC scenario (Torriani et al., 2007a). Management scenarios that are applied in the CropSyst simulations include nitrogen fertilizer and irrigation. In order to enhance variability of crop yields with respect to agricultural management, an experimental design is used. To this end, applications of nitrogen fertilizer and irrigation water are varied randomly[20]. Datasets of simulated yields for both climate scenarios are used to estimate production and yield variation functions that are presented in the subsequent section.

4.4 Empirical Analysis

Empirical analysis is restricted to two crucial inputs: nitrogen fertilizer (*N*) and irrigation water (*W*). The production function (*Y(X)*) is fitted to a square root functional form, which is the best specification of the *Y~N,W* relationship for corn yields on the eastern Swiss Plateau (Finger and Hediger, 2008). CropSyst outputs are used to estimate the production functions. Equations (4.9) - (4.10) and (4.11) - (4.12) are the production function estimations for soil 1 (*S1*) and soil 2 (*S2*) for the base and the 2050 scenario, respectively.

[20] Further details on data simulation are given in Finger and Schmid (2007a).

(4.9) *S1*/Base: $Y = 7872.7 + 158.3\,N^{1/2} + 77.8W^{1/2} - 6.7\,N - 2.4W + 0.2\,(NW)^{1/2}$

(4.10) *S1*/2050: $Y = 8368.3 + 180.4\,N^{1/2} + 96.6W^{1/2} - 8\,N - 1.2W + 2.5\,(NW)^{1/2}$

(4.11) *S2*/Base: $Y = 6601.9 + 313.1\,N^{1/2} + 67.1W^{1/2} - 10.5\,N - 2.5W + 0.4\,(NW)^{1/2}$

(4.12) *S2*/2050: $Y = 7053.1 + 309.9\,N^{1/2} + 71.6W^{1/2} - 9.6\,N - 1W + 3.5\,(NW)^{1/2}$

Y denotes corn yield (kg ha^{-1}), *N* nitrogen fertilizer (kg ha^{-1}), and *W* irrigation water (mm). Comparing the both scenarios, equations (4.9) - (4.10) and (4.11) - (4.12) show higher model intercepts and higher interaction parameters for $(NW)^{1/2}$ in the 2050 scenario, for both soils. In general, more favorable climatic conditions, the increased CO2 concentration and earlier sowing lead to higher model intercepts, i.e. to higher corn yield without any input application. The increase of the interaction parameters for $(NW)^{1/2}$ shows that irrigation becomes more important for optimal nitrogen uptake. In the base scenario, nitrogen uptake is sufficiently ensured by precipitation. However, in the 2050 scenario, where summer rainfall is reduced (cf. Table 4.1), optimal nitrogen uptake is only ensured if irrigation takes place.

Production functions are estimated using the robust regression technique of Reweighted Least Squares (see Rousseeuw and Leroy, 1987, for details). This estimation technique increases the accuracy of estimation. Ordinary least squares estimation becomes inefficient and unreliable for production function estimation if exceptional observations are included in the analysis. Exceptional yield observations are, for instance, caused by climatic extreme events, such as the summer drought of 2003 (Finger and Hediger, 2008). Furthermore, all estimations are corrected for heteroscedasticity using Feasible Generalized Least Squares regression. The estimation is conducted with the ROBUSTREG and the MODEL procedure of the SAS statistical package (SAS Institute, 2004), respectively.

Yield variation, $\sigma^{Y}(X)$, is defined as the absolute difference between expected and observed input-output combinations. Thus, absolute regression residuals of the production function estimation, $|e|$, are employed to estimate yield variation:

(4.13) $\sigma^{Y}(X)=|e|=\left|Y(X)-\hat{Y}(X)\right|$

Yield variation is, among other factors such as weather and soil conditions, affected by input use (Isik and Khanna, 2003). The relationship between yield variation and input use, $\sigma^{Y}(X) \sim N, W$, is modeled using a square root functional form. In this model, the intercept captures effects of soil and weather conditions on yield variation. Equations (4.14) - (4.15) and (4.16) - (4.17) show yield variation function estimates (for the base and the 2050 scenario) for *S1* and *S2*, respectively.

(4.14) *S1*/Base: $\sigma^{Y}(N,W)=613.5+25.8\,N^{0.5}-7.9W^{0.5}$

(4.15) *S1*/2050: $\sigma^{Y}(N,W)=660.9+28.1\,N^{0.5}-24.7W^{0.5}$

(4.16) *S2*/Base: $\sigma^{Y}(N,W)=409+39\,N^{0.5}-8.1\,W^{0.5}$

(4.17) *S2*/2050: $\sigma^{Y}(N,W)=468.5+39.8\,N^{0.5}-20.3W^{0.5}$

For both soils, the intercept of the yield variation functions increases from the base to the 2050 scenario. Thus, if neither irrigation nor nitrogen fertilizer application takes place, CC leads to higher yield variation. In general, the application of nitrogen fertilizer increases ($\sigma^{Y}_{N^{0.5}}>0$) and irrigation decreases ($\sigma^{Y}_{W^{0.5}}<0$) yield variability. $\left|\sigma^{Y}_{W^{0.5}}\right|$, the propensity of irrigation to reduce yield variation, increases from the base to the 2050 scenario for both soils. Due to higher temperatures and lower summer precipitation, irrigation is a more risk decreasing activity in 2050 than it is currently. In contrast, the effect of nitrogen on yield variation, $\sigma^{Y}_{N^{0.5}}$, is not affected by CC. However, conclusions on the impact of CC on yield levels, yield variation and profitability of SST can be drawn if and only if utility maximizing input and output levels are calculated.

4.5 Results

Maximization of expected utility, as described in section 4.3, requires assumptions of input and output prices and the coefficient of risk aversion. These assumptions as well as coefficient estimates for production and yield variation functions (section 4.5) are employed to solve first order conditions (eqn. 4.5). In order to restrict our analysis to effects induced by CC we apply similar input and output prices for both analyzed scenarios. We assume prices[21] of CHF 0.185 kg^{-1} , CHF 0.91 kg^{-1} and CHF 0.6 mm^{-1} for corn, nitrogen fertilizer and irrigation, respectively (Finger and Schmid, 2007). Moreover, the analysis is restricted to one numerical example of constant risk aversion, γ = 0.5. Sensitivity analyses of Swiss corn yields for different scenarios of climate change, prices and risk aversion is given in Finger and Schmid (2007, 2008). Derived optimal levels of input use, expected utility, yield and yield variation for both soils are presented in Table 4.3.

Table 4.3: Optimal levels of input use, expected utility, yields and yield variation.

Soil Type - Climate Scenario	Nitrogen (kg/ha)	Irrigation water (mm)	Expected Utility (per ha)	Yield (kg / ha)	Yield variation (kg / ha)
S1 -Base	40.07	53.45	1540.11	9055	718.81
S2 -Base	91.60	42.30	1486.26	8986	729.27
Absolute Diff. between *S1* and *S2*	51.53	11.15	53.85	69	10.46
S1 - 2050	61.61	210.71	1754.09	10729	522.10
S2 - 2050	137.93	208.49	1685.66	10788	643.21
Absolute Diff. between *S1* and *S2*	76.32	2.22	68.43	59	121.11

Source: Own calculations

Table 4.3 shows that optimal fertilizer application for both climate scenarios is higher for *S2* than for *S1*. This is because of lower soil fertility of *S2* (cp. Table 4.2). For both soil types, application of both inputs, irrigation water and nitrogen, is higher in the 2050 than in the base scenario. Yields increase and yield variations decrease from the base to the 2050 scenario. Thus, expected utility is higher in 2050 for both soils. Moreover, Table 4.3 shows that absolute differences between *S1* and *S2* for expected utility, nitrogen application and yield variations increases from the base to the 2050 scenario. CC causes increasing differences between soils with respect to optimal input use and expected utility.

[21] Due to market liberalization Swiss input and output prices are assumed to decline in future. Thus, lower than current Swiss prices are assumed in this analysis.

In order to analyze the impact of CC on the profitability of SST adoption, we simulate utility differences of site specific and conventional management as described in Section 4.3. Input application for conventional management follows the three scenarios on soil information levels (a-c) that are described in section 4.3. For site specific management, optimal inputs such as presented in Table 4.3 are applied for each site (eqn. 4.6). Average differences in expected utility between site specific and conventional management (eqn. 4.8) are shown in Table 4.4.

Table 4.4: Expected utility differences between site specific and conventional management for the base and the 2050 scenario.

Climate Scenario	**Expected utility differences between site specific and conventional management**		
	Zero Information (a)	Rough Information (c)	Ratio of S1/S2 known (b)
$\Delta E(U(S,C))$ - Base	10.49	8.33	6.22
$\Delta E(U(S,C))$ - 2050	13.71	11.36	9.17

Note: (a), (b) and (c) denote different levels on soil information. All expected utility differences, and differences between the Base and the 2050 scenario, are significant at the 0.05 level (using the one sample Wilcoxon and the signed rank test, respectively). Source: Own calculations

A higher level of information about soil composition leads to smaller differences in expected utilities between site specific and conventional management (Table 4.4). This is due to smaller differences in input application between site specific and conventional management for higher levels of soil information. Thus, the incentive to adopt site specific management decreases for higher knowledge of soil composition.

Moreover, Table 4.4 shows increasing differences in expected utilities between site specific and conventional management from the base to the 2050 scenario. The relative increase in this difference is between thirty and fifty percent. Further calculations (not shown) with different states of soil information and different composition of soils indicate increases in the same range. However, relative to the levels of expected utility given in Table 4.3, the expected utility increase that is caused by the adoption of site specific management is small for both climate scenarios (smaller than one percent). The calculations of utility differences between site specific and conventional farming presented in Table 4.4 do not include adoption costs. These costs and expected effects on SST adoption are discussed in the subsequent section.

4.6 Discussion and Conclusions

Our case study shows increasing differences in expected utilities between site specific and conventional management from the base to the 2050 scenario. Thus, the incentive to adopt site specific management, ceteris paribus, increases. This is in particular due to increasing differences between soils with respect to optimal nitrogen application and corn yield variation (Table 4.3). Moreover, corn yield variation (i.e. production risk) for both soils is smaller in the 2050 than in the base scenario. Lower production risk leads, in general, to higher rates of SST adoption (Isik and Khanna, 2002). In order to validate our results for Swiss agriculture at large, further soil types, crops and CC scenarios should be considered.

Adoption costs are omitted in the analysis of SST profitability presented in this study. This is due to the fact that site specific management is inexistent in Switzerland yet. There is no information on costs available. For Illinois, Khanna et al. (2000) report costs of about CHF 10 per hectare and year[22] for hiring service that applies inputs at a varying rate in the field. Due to the lack of experience and the lack of service suppliers we expect, however, higher prices for this service in Switzerland. Taking expected utility differences between site specific and conventional management into account (Table 4), SST adoption is expected to remain minor in current climatic conditions. However, these costs for hiring service are assumed to decline in the following years because of technical progress (Khanna et al., 2000; Auernhammer, 2002) and improvements of landscape and plant related indicators (Anselin et al., 2004; Pampolino et al., 2007). Both, higher differences in expected utility between site specific and conventional management and lower prices for SST adoption lead to higher incentives for SST adoption in future.

[22] KHANNA et al. (2000): 5.157 $/acre (assumed exchange rate: USD/CHF = 1.2)

CC will affect the incentive of SST adoption because effects of CC on crop production particularly depend on soil characteristics (Eitzinger et al., 2003; Wassenaar et al., 1999). Therefore, we expect increasing spatial variability of soils with respect to input use and yield variation which is supported by this case study. This leads, ceteris paribus, consequentially to higher shares of site specific management in crop production under CC. Even though, this case study does not directly address environmental impacts of site specific management practice, it is indicated by other studies that the feedback loop between CC and crop production can lead to a reduction of emissions and pollution caused by agriculture and result in a more sustainable use of natural resources. Only if further research takes into account a broad range of farmers' adaptation options, such as the here presented adoption of site specific management, the impacts of CC on agriculture can be sufficiently assessed.

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Chapter 5

Irrigation as adaptation strategy to climate change – a biophysical and economic appraisal for Swiss maize production

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Abstract

The impact of climate change on Swiss maize production is assessed using an approach that integrates a biophysical and an economic model. Simple adaptation options such as shifts in sowing dates and adjustments of production intensity are considered. In addition, irrigation is evaluated as an adaptation strategy. It shows that the impact of climate change on yield levels is small but yield variability increases in rainfed production. Even though the adoption of irrigation leads to higher and less variable maize yields in the future, economic benefits of this adoption decision are expected to be rather small. Thus, no shift from the currently used rainfed system to irrigated production is expected in the future. Moreover, we find that changes in institutional and market conditions rather than changes in climatic conditions will influence the development of the Swiss maize production and the adoption of irrigation in the future.

5.1 Introduction

Climate change is expected to affect agriculture in different ways and to a different extent in different parts of the world and in different agro-ecosystems (Olesen and Bindi, 2002, Parry et al., 2004). The consequences will depend on local climatic and soil conditions, on the political and economic framework, and on the farmers' management and adaptation decisions. The latter entail several options to cope with climate change on the field and farm level (see, for instance, Risbey et al., 1999, Smit and Skinner, 2002). Apart from agronomic aspects, these options involve economic decisions taken by individual farmers who optimize their production by adapting their use of fertilizers, pesticides and irrigation water to changing climatic, political and economic conditions.

The goal of this study is to analyze impacts of climate change on the maize production at the Swiss Plateau taking different climate and price scenarios into account. We consider two simple adaptation options on the field level: (a) shifts in sowing dates and (b) changes in the production intensity. Building on this background, we further evaluate irrigation as a strategy to cope with climate change.

The Swiss Plateau is the major production region for cereals in Switzerland. Changes in climatic conditions in this region are expected to particularly affect the production of spring-sown cereals such as maize. Due to elevated temperatures and reduced summer rainfalls, maize yields might be considerably reduced and become more variable if no adaptation measures are taken (Torriani et al., 2007a, b). Using a crop simulation model, Torriani et al. (2007a) evaluated different adaptation strategies for the Swiss maize production. Their analysis shows that earlier sowing, changes in thermal requirements and irrigation can compensate (or even over-compensate) climate change induced effects on yield levels and yield variability.

Some adaptation options such as shifts in sowing dates might be implemented without costs for the farmers. Other options such as the implementation of irrigation farming involve costs and thus require an assessment that is also based on economic grounds. To examine this problem, we apply an approach that integrates biophysical and economic modeling. This particularly facilitates the analysis of the combined effects of future changes in climate and agricultural prices on optimal yield levels, yield variability and the economic benefits of irrigation systems. In contrast to other approaches that analyze potential crop yields or production systems under unadapted management conditions, our approach compares (economically) optimal crop yields under current and future climatic conditions (see Finger and Schmid, 2008, for a discussion on other modeling approaches).

The current situation shows that only about five percent of the cultivated acreage in Switzerland is irrigated. It is mainly located in alpine dry valley regions and used to the largest extent in grassland, vegetables, vine and fruit production. In contrast, cereals are currently irrigated only to a very small extent (Weber and Schild, 2007). However, climate change is expected to increase the agricultural water demand. As a consequence, competition for water among ecosystems and different economic sectors such as industry and agriculture is expected to increase in the future (Bates et al., 2008, OcCC, 2007, 2008). Therefore, the analysis of the potential of irrigation as an adaptation option in Swiss cereal production is crucial for the optimal future design of agricultural extension as well as policy measures that support farmers' adaptation to climate change and environmental protection.

According to previous results (Finger and Schmid, 2008), climate change is expected to have small positive effects on winter wheat production, which represents the majority of the Swiss cereal production. Moreover, irrigation is expected to lead neither to significantly higher winter wheat yield levels nor to economic benefits in changed climatic conditions because relevant spring rainfalls are expected to decrease only slightly (Finger and Schmid, 2008, Torriani et al., 2007a). The present analysis is therefore focused on maize that is the most important spring-sown cereal and covers about 12% of the total cereal production acreage (SBV, 2006). Globally, maize is one of the most important cereals for human and animal nutrition. Accordingly, it will be important to have analyses of climate change impacts on maize production and potential adaptation strategies in different parts of the world. Our analysis might particularly indicate the direction of climate change impacts on maize production and consequences for agricultural water demand in other Middle-European regions that face similar climatic and production conditions.

Using a combination of biophysical and economic modeling, our analysis reveals that the adoption of irrigation might result in higher and less variable maize yields under future climatic conditions, while the expected economic benefits to the farmers are rather small.

5.2 Data and Model Description

In the following section, we present our modeling approach that integrates a biophysical and an economic model. The biophysical model is used to simulate yield responses to the crucial agricultural inputs nitrogen fertilizer and irrigation water in current and future climatic conditions. In the economic model, input use is optimized in order to maximize farmers' certainty equivalents of the farmer's quasi-rent. This approach takes into account both yield levels and yield variability. To link the biophysical simulation and the economic optimization model, crop production and yield variation functions are estimated[23].

5.2.1 Biophysical Model and Climate Scenarios

We use the deterministic crop yield simulation model CropSyst to mimic the relationship between maize yields and input use for current and future climatic conditions. It models above- and below-ground processes (e.g. the soil water budget, soil-plant nitrogen budget, crop phenology, canopy and root growth, and crop yield) on a daily time step (see Stöckle et al., 2003, for details). In CropSyst, these processes are simulated in response to crop and soil characteristics, daily weather data, and management options[24].

In this study, we consider current climate conditions as well as three different scenarios of climate change. To represent current climate conditions, we use weather data from meteorological stations at the eastern Swiss Plateau for the years 1981 to 2003. The three climate change scenarios in our analysis are taken from Frei (2005), whose projections were performed within the scope of the PRUDENCE project (Christensen et al., 2002) on

[23] More detailed descriptions and discussions of the modeling approach are given in Finger and Schmid (2008) and Torriani et al. (2007a).

[24] Model calibration and settings for maize production at the Swiss Plateau are presented in Torriani et al. (2007a).

the basis of simulations with 16 different scenario-model combinations. The climate projections used in this study represent the median of these ensemble simulations for the years 2030 and 2050 plus the 97.5% percentile for the year 2050. These scenarios are tagged in the following as 2030, 2050 and 2050X. The last scenario represents a rather extreme assumption of climate change, whereas the first two scenarios assume moderate changes in climatic conditions (Table 5.1).

Table 5.1. Description of Climate Scenarios.

Description	2030				2050				2050X			
	DJF	**MAM**	**JJA**	**SON**	**DJF**	**MAM**	**JJA**	**SON**	**DJF**	**MAM**	**JJA**	**SON**
Temperature (in °C)	+ 1.0	+ 0.9	+ 1.4	+ 1.1	+ 1.8	+ 1.8	+ 2.7	+ 2.1	+ 3.4	+ 3.3	+ 4.7	+ 3.5
Precipitation (relative change)	1.04	1.00	0.91	0.97	1.08	0.99	0.83	0.94	1.21	0.89	0.69	0.86
CO2 concentr. (in ppm)	437-475				495-561				495-561			

Note: Scenarios for Northern Switzerland. DJF: December-February; MAM: March-May; JJA: June-August; SON: September-November. CO2 concentrations for the Base scenario range from 339 to 379 ppm. CO2 concentrations vary randomly within the defined range for each climate scenario. Source: IPCC (2000) and Frei (2005).

Based on today's weather data and the anomalies of temperature and precipitation, sets of future weather data are generated using the stochastic weather generator LARS-WG (Semenov et al., 1998). To enable meta-modeling analysis and avoid distortions due to dynamic effects, all simulations are conducted using identical starting conditions. We assume a representative soil for the Swiss Plateau that is characterized by a texture with 38% clay, 36% silt, 26% sand, as well as by a soil organic matter content at 2.6% weight in the top soil layer (5 cm) and 2.0% in lower soil layers.

Sowing dates and expected dates of maturity are given in Table 5.2. For the climate change scenarios, we used earlier sowing dates because this reduces negative effects of climate change such as increased heat and drought stress. As a consequence of increased temperatures, maturity periods are shorter in the climate change than in the Base scenario. Thus, sowing and harvesting dates as well as the length of the maturity period are expected to change considerably in the future.

Table 5.2. Sowing and expected maturity dates.

Climate Scenario	Base	2030	2050	2050X
Sowing Date	10th May (130)	7th May (127)	4th May (124)	30th April (120)
Expected Day of Maturity	17th September (263)	4th September (250)	28th August (240)	18th August (230)
Expected Length of Maturity Period	133 d	123 d	116 d	110 d

Note: Numbers in brackets are days of year. Sowing dates for current and future climate follow Dubois et al. (1999) and Torriani et al. (2007a). Expected days of maturity are derived from CropSyst simulations.

The management scenarios for the CropSyst simulations include application of nitrogen and irrigation water. Depending on the applied amount of nitrogen, three to four fertilizer applications are made at different stages of the cropping season. The annual amount of applied nitrogen ranges from 0 to 320 kg ha^{-1}. To simulate irrigation, we chose the automatic irrigation option of CropSyst. Thus, irrigation is triggered as soon as soil moisture is lower than a specific user-defined value. The degree of soil moisture is expressed as a value between 0 (permanent wilting point) and 1 (field capacity). When soil moisture falls below the previously defined value, water is added to the soil until field capacity is reached with an upper limit of 20 mm per irrigation event. For each year, one simulation is conducted without application of fertilizer and irrigation. Furthermore, to set up an experimental design, the amount of fertilizer and the degree of soil moisture that triggers irrigation was varied randomly. To allow for comparability of the results, the simulated experimental framework is equal for each climate scenario. This data simulation leads to individual data sets for the different climate scenarios that contain information of maize yield and the amount of applied input for each observation[25].

5.2.2 Production and Yield Variation Functions

This output from the biophysical simulation is used to estimate production and yield variation functions. These functions are simple analytical descriptions of yield and yield variability responses to nitrogen and irrigation, which are used to integrate these biological response processes in the economic allocation model. Thus, the estimated

[25] Depending on the climate scenario, these data sets contain between 527 and 531 observations. Data sets are available from the authors upon request.

functions are the linkage between the biophysical model and the economic model. The per-hectare production function, $Y = Y(N,W)$, is fitted to a square root functional form[26]:

$$Y = \alpha_0 + \alpha_1 \cdot N^{1/2} + I \cdot \alpha_2 \cdot W^{1/2} + \alpha_3 \cdot N + I \cdot \alpha_4 \cdot W + I \cdot \alpha_5 \cdot (N \cdot W)^{1/2} \qquad (5.1)$$

Y denotes maize yield (kg ha^{-1}), N the amount of nitrogen applied (kg ha^{-1}), W the irrigation water applied (in mm), and I is an indicator to distinguish rainfed ($I = 0$) and irrigated ($I = 1$) farming systems. The α_i's are parameters that must satisfy the subsequent conditions to ensure decreasing marginal productivity of each input factor: $\alpha_1, \alpha_2 > 0$ and $\alpha_3, \alpha_4 < 0$. Furthermore, if $\alpha_5 > 0$, the two input factors are complementary. They are competitive if $\alpha_5 < 0$, while $\alpha_5 = 0$ indicates independence of the two input factors.

Yield variation, $\sigma_Y(N,W)$, is defined as the absolute difference between observed yields (i.e. yields simulated with CropSyst) and expected yields (i.e. yield values on the production function) in our analysis. Thus, for a single observation, yield variation corresponds to the absolute residual of the regression analysis. It is modeled with a yield variation function as follows:

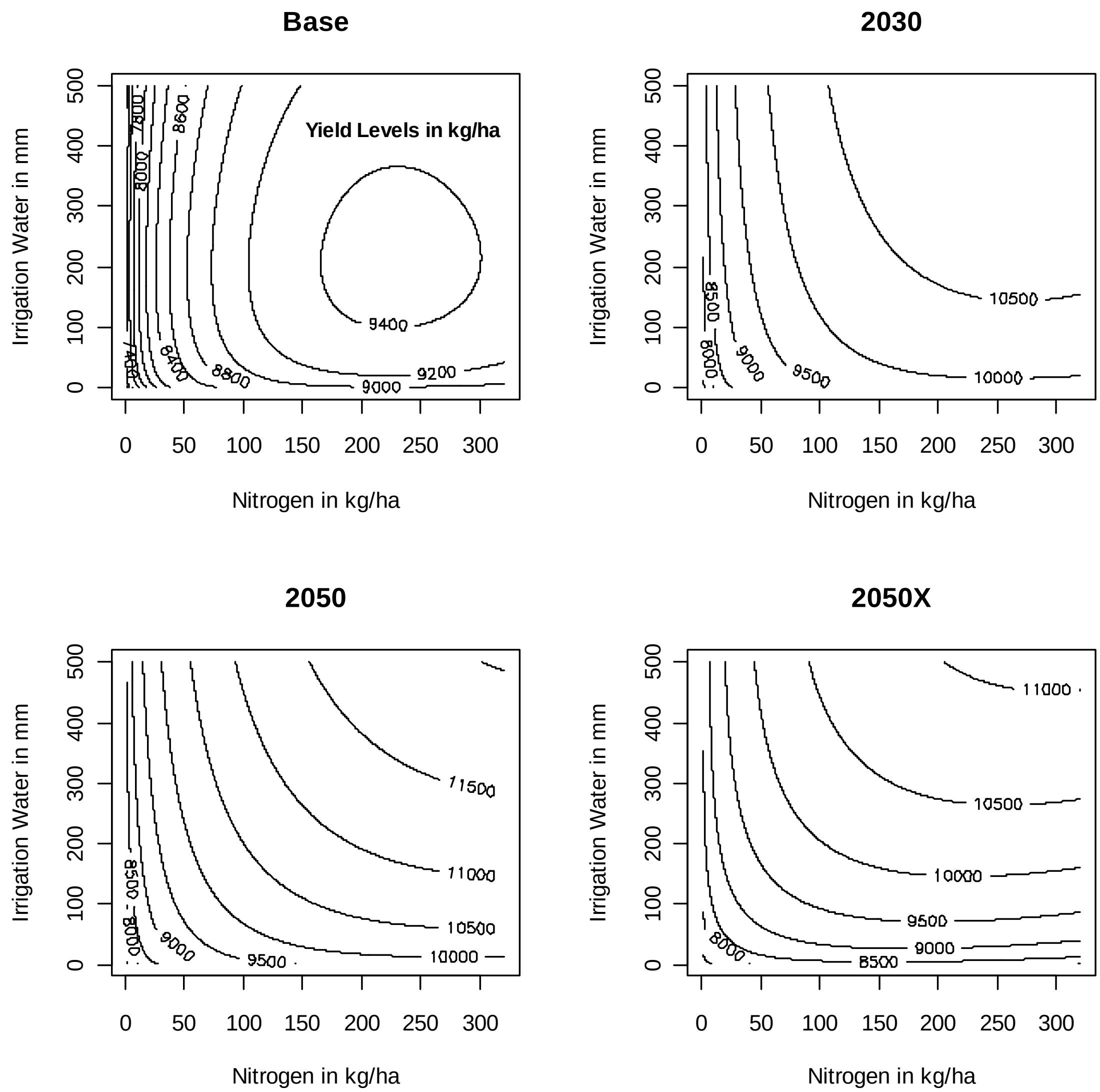
$$\sigma_Y(N,W) = \beta_0 + I \cdot \beta_1 \cdot W^{0.5} + \beta_2 \cdot N^{0.5} \qquad (5.2)$$

Shifts in the intercept, β_0, capture effects of changes in weather conditions on yield variation across different climate scenarios. β_1 and β_2 quantify the influence of irrigation and nitrogen application on yield variation. An input is risk decreasing if $\beta_i < 0$ and risk increasing if $\beta_i > 0$, respectively.

For each climate scenario, a single production and yield variation function is estimated. The estimation results[27] of these functions are presented as contour plots in Figure 5.1 and 5.2.

[26] The selection criteria for the applied functional forms and the estimation methodology are described in Finger and Hediger (2008) and Finger and Schmid (2008).
[27] Coefficient estimates are available upon request from the authors.

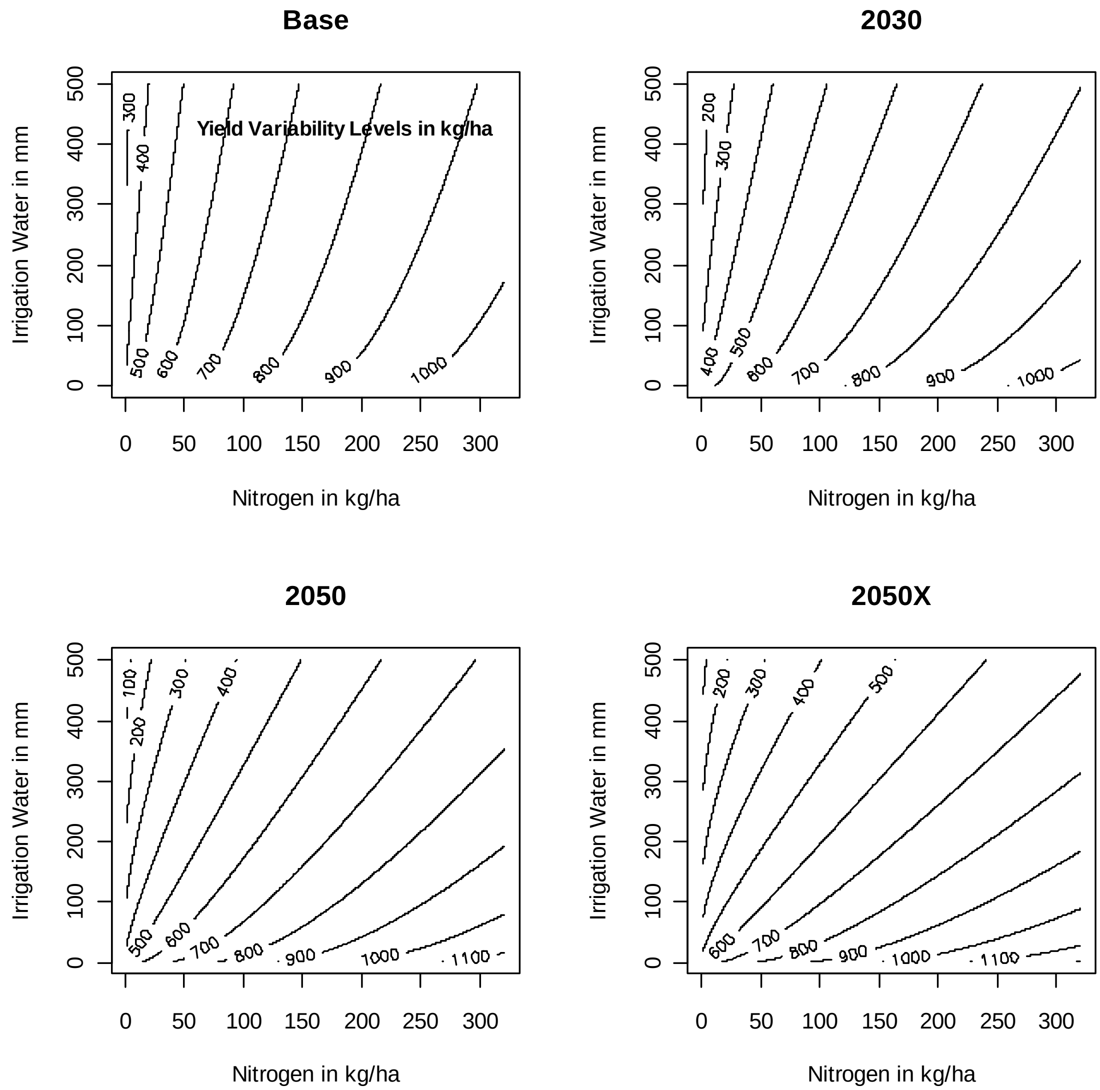
Figure 5.1. Contour plots of the production functions: crop yield as function of nitrogen and irrigation water



Contour plots (i.e., isoquants) for the production functions show that future maize yields, ceteris paribus, exceed current levels (Figure 5.1). For constant levels of nitrogen application without irrigation, yield levels increase from the Base to the 2050 scenario, but decrease from the 2050 to the 2050X scenario. Increasing yield levels are caused by higher CO2 concentrations and the applied shifts in sowing date. For the 2050X scenario, temperature increases and reductions in the amount of summer rainfall offset the benefits of increased CO2 concentrations. Moreover, it shows that irrigation water becomes a more important production factor in the future. In current climatic conditions, the crop yield response to irrigation water is small because water is no limiting factor in maize production at the Swiss Plateau. Increasing temperatures and lower amounts of summer rainfall in the climate change scenarios reduce the water available to the plant and thus increase the yield responses to irrigation water. While crop yields are nearly independent from irrigation water in the Base scenario, the production factors nitrogen and irrigation water become more complementary in the climate change scenarios. This indicates that future maize yields might exceed current levels if sufficient water availability is ensured by supplemental irrigation.

In Figure 5.2, contour plots of the yield variation functions are presented. It shows that nitrogen application increases, but irrigation reduces, ceteris paribus, yield variability. Moreover, climate change increases yield variability. For constant levels of nitrogen application without irrigation, yield variability increases from the Base and 2030 scenarios to the 2050 and 2050X scenarios. However, the propensity of irrigation to reduce maize yield variability increases from the Base to the 2050X scenario because increases in the applied amount of irrigation water lead to larger reductions of yield variability in the climate change scenarios than in the Base scenario. Thus, expanded application of irrigation might counteract climate changed induced increases of yield variability in the future.

Figure 5.2. Contour plots of the yield variation functions: crop yield variability as function of nitrogen and irrigation water



5.2.3 The Economic Model

The production and yield variation functions are integrated in the economic model to derive the optimal input allocation for different climate scenarios. To this end, the economic model is based on the maximization of the certainty equivalent (CE). This is a certain level of payoff which provides a (risk averse) decision maker with the same benefit as a higher but uncertain level of payoff, and is defined as follows:

$$CE = E(\pi) - RP \tag{5.3}$$

Where $E(\pi)$ is the expected quasi-rent π (revenue minus variable costs) and *RP* is the risk premium, which is the difference between the expected quasi-rent and the certainty equivalent. The expected quasi-rent is defined as:

$$E(\pi) = pE(Y(N,W)) - Z_N N - Z_W W \tag{5.4}$$

Where Z_N and Z_W stand for the input prices for nitrogen *N* and irrigation water *W*, respectively, and *Y(N,W)* denotes the production function.

In our analysis, the risk premium is defined as $RP = \gamma p \sigma_Y(N,W)$. Where $p\sigma_Y(N,W)$ is the standard deviation of the quasi-rent and γ is the coefficient of absolute risk aversion that is chosen as 0.5 indicating risk-averse behavior. Accordingly, our optimization problem is defined as follows:

$$\max_{N,W} CE = pE(Y(N,W)) - Z_N N - Z_W W - \gamma p \sigma_Y(N,W) \tag{5.5}$$

The certainty equivalent is maximized subject to the production function constraint *Y(W,N)*. Input prices are restricted to variable costs. Thus, total variable costs are defined as the variable nitrogen costs (nitrogen applied x nitrogen price) plus the variable irrigation costs (irrigation water applied x irrigation water price). Other costs are assumed constant and thus irrelevant for the optimal input combination. Accordingly, the first order conditions for optimal input use are:

$$\frac{\partial Y(N^*,W^*)}{\partial N^*} - \frac{Z_N}{p} - \gamma \frac{\partial \sigma_Y(N^*,W^*)}{\partial N^*} = 0$$

and (5.6)

$$\frac{\partial Y(N^*,W^*)}{\partial W^*} - \frac{Z_W}{p} - \gamma \frac{\partial \sigma_Y(N^*,W^*)}{\partial W^*} = 0$$

Where, N^* and W^* denote the optimal input levels of *N* and *W*, respectively, resulting in the highest certainty equivalent of the quasi-rent.

To compare irrigation and rainfed farming, Equation 5.6 is solved for both irrigation and non-irrigation farming independently. If rainfed farming is assumed, production and yield variation functions only contain nitrogen but no irrigation water. The farmer’s economic benefit of the adoption of irrigation farming, expressed in monetary values, is the difference between optimal (i.e. maximum) certainty equivalents for irrigated farming, $CE^{*}(I{=}1)$, and rainfed farming, $CE^{*}(I{=}0)$:

$$DCE = CE^{*}(I = 1) - CE^{*}(I = 0) \tag{5.7}$$

This measure is used in our analysis to assess the expected relative advantage of irrigation farming.

5.2.4 Price scenarios

In order to derive optimal levels of input, output and utility, information about input and output prices is required. Current price levels and price scenarios for maize, nitrogen and irrigation water are given in Table 5.4.

In the first price scenario (P1) that all price levels are assumed to remain on current levels. Because current agricultural price levels in Switzerland are much higher than in other European countries, we additionally employ a price scenario using current maize and nitrogen price levels in the European Union (P2). This scenario reflects expected decreases in price levels if market liberalization, e.g. with the European Union, takes place.

Furthermore, we consider two scenarios with higher water prices (0.12 CHF/m^3) caused by, for instance, higher withdrawal fees or increasing use of ground- instead of surface water in the future. In drought years, as it was the case in 2003, access to surface water might be restricted and groundwater has to be used instead, leading to higher withdrawal fees and pumping costs (ProClim, 2005). Combining the higher water price with the two price scenarios (P1 and P2) presented above, this leads to the scenarios P3 and P4 (Table 5.4). In addition, we study the effect of changing water prices on the economic benefits of irrigation farming as well as on the optimal amount of irrigation water using a sensitivity analysis.

Table 5.4: Price Scenarios (in CHF).

Price scenario	Maize kg^{-1}	Nitrogen kg^{-1}	Irrigation (mm per ha)
P 1	0.396	1.33	0.6
P 2	0.185	0.91	0.6
P 3	0.396	1.33	1.2
P 4	0.185	0.91	1.2

Note: Current price levels for maize and nitrogen in Switzerland and the EU refer to the year 2006, following Hartmann et al. (2007) and Finger and Schmid (2008).

5.3 Results and Discussion

For the price scenario P3, Table 5.5 shows optimal factor inputs, yield levels, yield variation, coefficients of variation and certainty equivalent income levels for both rainfed and irrigated farming under different climate conditions – i.e., for the Base scenario and the 3 climate change scenarios. It shows increasing yield levels for both irrigated and rainfed farming from the Base to the 2030 scenario. Thereafter, yield levels are expected to decrease in rainfed farming systems. In particular, the yield level in the 2050X scenario is expected to be considerably below the current level. Moreover, the relative yield variability (i.e. the coefficient of variation) in rainfed production systems is expected to increase with more pronounced climatic changes.

In irrigation farming systems, future yields are expected to be above current levels because climate change provides an economic incentive to expand irrigation activities. Furthermore, increases in the optimal amount of applied irrigation water reduce yield variability in the future. As a consequence, also relative yield variability is expected to decrease in irrigated maize farming systems.

A comparison of optimal input levels of nitrogen between rainfed and irrigated farming systems reveals different adaptation strategies. In rainfed production systems, reduced summer rainfalls lead to a reduction of the optimal production intensity from the Base and the 2030 scenarios to the 2050 and 2050X scenarios. In contrast, an increased application of nitrogen, i.e. a more intensive production, is an optimal response to climate change if irrigation is available[28].

By integrating the possibility to adjust production intensity, our modeling approach avoids the overestimation of economic losses due to climate change. Even though optimal yield levels and yield variations between irrigated and rainfed farming systems considerably differ for the climate change scenarios, the differences in certainty equivalents between those farming systems remain relatively small (Table 5.5).

Table 5.5: Optimal Input Levels, Certainty Equivalents, Yields and Yield Variation.

Climate Scenario	Nitrogen ($kg\ ha^{-1}$)	Irrigation Water (mm)	Certainty Equivalents ($CHF\ ha^{-1}$)	Yield ($kg\ ha^{-1}$)	Yield Variation ($kg\ ha^{-1}$)
I=0 (rainfed)					
Base	111.50	0	3147.22	8732.73	820.63
2030	130.49	0	3427.46	9508.07	829.65
2050	125.35	0	3343.07	9320.33	914.33
2050X	63.85	0	2908.07	7990.14	864.08
I=1 (irrigation)					
Base	114.10	87.48	3286.20	9188.89	749.36
2030	138.82	97.64	3579.95	10160.92	717.74
2050	178.45	252.81	3724.53	11109.26	677.83
2050X	121.30	265.70	3473.93	10277.88	581.75
Difference between I=1 and I=0					
Base	2.60	87.48	138.98	456.16	-71.27
2030	8.33	97.64	152.49	652.85	-111.91
2050	53.10	252.81	381.46	1788.93	-236.50
2050X	57.45	265.70	565.86	2287.74	-282.33

Note: The price scenario reported is P3. The coefficient of variation is calculated as the ratio of the yield variation and the yield level. 2030, 2050, and 2050X denote climate scenarios that are described in Table 5.1.

Expected changes, relative to the Base scenario, in yield levels and yield variability for all price scenarios are summarized in Figure 5.3. In rainfed production, yield levels are higher in the 2030 and 2050 scenarios but lower in the 2050X scenario. Moreover, yield variability is expected to increase for all but the 2030 scenario assuming current Swiss price levels[29]. However, the expected increase in relative yield variability is relatively small. The coefficient of variation (CV) increases, in maximum, from 0.09 in the Base to

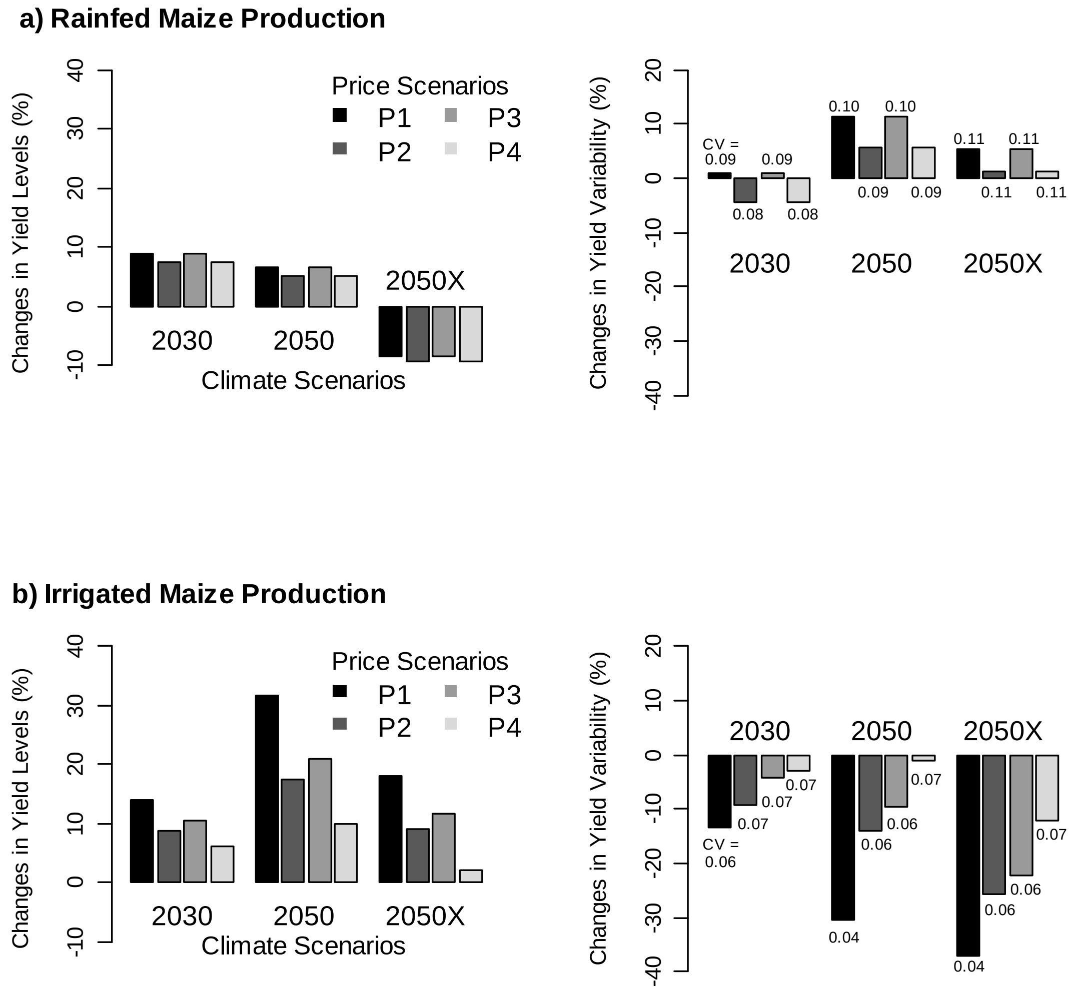
[28] Adaptation strategies towards more intensive production by increasing nitrogen application might be limited in practice due to cross compliance components in agri-environmental policy.

[29] No differences between the scenarios P1/P3 and P2/P4 exist for rainfed production because water prices are not relevant.

0.11 in the 2050X scenario. A higher maize price (comparing the P1 and the P2 price scenario) leads to higher yield levels and higher yield variability as the optimal amount of nitrogen application is augmented.

For irrigated maize production, future yield levels are expected to increase and yield variability is expected to decrease for all price scenarios. As previously discussed for the yield variation functions, irrigation becomes more important in coping with the climate change induced increases of farming risk. Thus, climatic changes lead to higher incentives for the expansion of irrigation activities that increase, ceteris paribus, yields and decrease yield variability. However, it shows that the results for irrigated farming are highly sensitive to changes in price levels. A decreasing maize price (comparing P1 and P2) as well as an increase of the water price (comparing P1/P3 and P2/P4) reduce the incentives to expand irrigation activities and thus result in smaller yield increases and smaller decreases of yield variability.

Figure 5.3. Relative changes to the Base scenario: yield levels, absolute and relative yield variability for 3 climate change and 4 price scenarios.



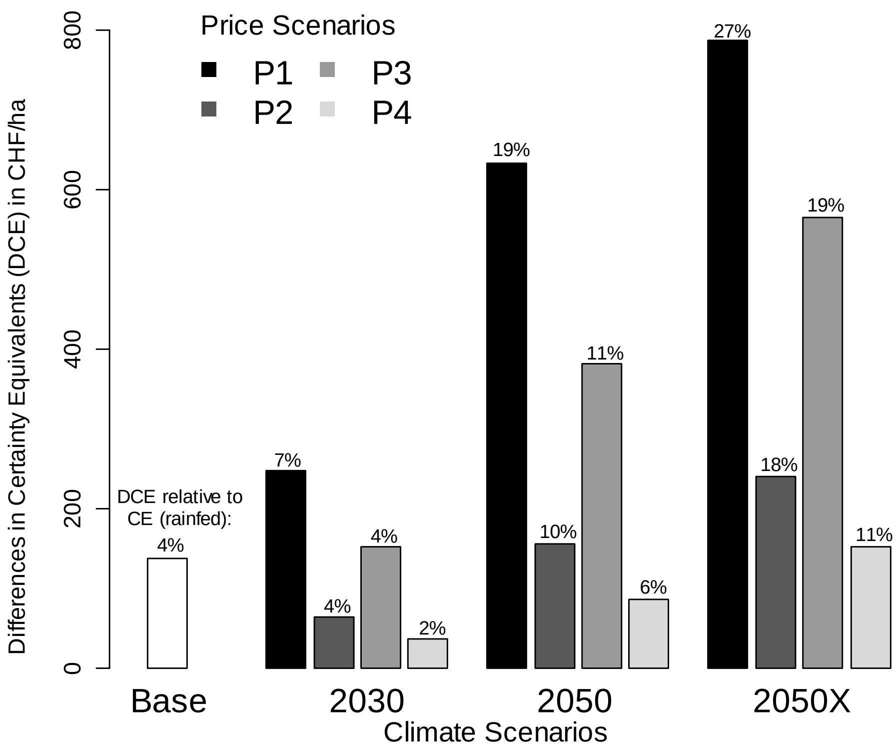
Note: Changes are relative to the Base scenario. CV denotes the coefficient of variation. 2030, 2050, and 2050X denote climate- and P1-P4 denote price scenarios that are described in Table 5.1 and Table 5.4, respectively.

In order to analyze whether the increasing differences in yield levels and yield variability between irrigated and rainfed maize production might result in a frequent adoption of irrigation farming systems in the future, differences in certainty equivalents (DCE) are analyzed (see Equation 5.7). These differences reflect the expected annual economic benefits enabled by the adoption of irrigation farming. The DCE increases constantly from the 2030 to the 2050X scenario for all price scenarios, as shown in Figure 5.4.

For the price scenario P1, future DCEs exceed the current value considerably. Higher temperatures and reductions of summer rainfalls increase, ceteris paribus, the profitability of irrigation in maize farming. However, reduced output prices (scenario P2) as well as higher water prices (P3, P4) result in much smaller expected rises in DCE. Especially for the price scenario P4, which assumes a low maize but high water price, future DCEs exceed current levels only for the 2050X scenario. The ratio of future DCEs to the corresponding certainty equivalents in rainfed production, range between 2% and 27% and increase constantly from the 2030 to the 2050X scenario.

In our modeling approach, estimated economic benefits of irrigation farming are already reduced by considering other adaptation options, i.e. shifts in sowing dates and changes in production intensity.

Figure 5.4. Absolute and relative certainty equivalent differences between irrigated and rainfed maize farming.



Note: DCE and CE differences in certainty equivalents and certainty equivalents. Relative differences are given in % of the certainty equivalents in rainfed production. 2030, 2050, and 2050X denote climate- and P1-P4 denote price scenarios that are described in Table 5.1 and Table 5.4, respectively.

To compare the estimated benefits with the cost of the adoption of irrigation farming we consider cost calculations of 3 irrigation projects at the Swiss Plateau that have been recently realized[30]. These calculations show annual fixed costs (amortization, maintenance, etc.) of irrigation systems between about 800 and 2000 CHF per hectare and year[31]. They are highly sensitive to the assumed asset depreciation rates, which might

[30] Personal communication Andreas Schild, Swiss Federal Office for Agriculture, Bern.
[31] Current water withdrawal fees range from unique user fees to annual fees and differ considerably across cantons, both with respect to the level of fees and the period that is charged for (Weber and Schild, 2007).

be larger in practice than assumed in our assessment[32]. Moreover, the effective adoption costs will be heterogeneous among irrigation projects due to differences, for instance, in farm size, soil and farm characteristics, access to irrigation water as well as infrastructure endowments (Kulshreshtha and Brown, 1993, Negri et al., 2005). Thus, the above estimates of annualized fix costs indicate that the adoption costs the most likely exceed the estimated economic benefit for current as well as future climatic conditions (cf. Figure 5.4). As a consequence, our results suggest that future adoption rates of irrigation in maize farming systems will remain small even in changed climatic conditions.

The development of governmental support (e.g. share of covered costs, allocation practice) will also be a key driver of farmers' adoption decisions in the future. At present, up to 50% of the adoption costs for an irrigation system can be covered by national and cantonal bodies[33]. However, the current practice of these support payments at the Swiss Plateau is restrictive and focused on cooperative projects. Altogether, our results indicate that the future demand for irrigation water in Swiss maize production might be determined by the development of price levels and governmental support rather than by climate change.

Finally, the future profitability of irrigation and the demand for irrigation water in maize farming systems are expected to be sensitive to water prices. To analyze these sensitivities, we show in Figure 5.5 the DCE levels and the optimal amounts of irrigation water for different water prices. Assuming current EU prices for maize and nitrogen (price scenario P2), we vary the water price stepwise in a range of -50% to +250% of the current level. Higher water prices might reflect enhanced competition for water among different economic sectors or an intensified use of ground-water. Moreover, higher withdrawal fees might reflect the internalization of negative externalities such as, for instance, water pollution from nutrients and pesticides, habitat damages by abstraction of water as well as impacts on quantity and quality of soils (Baldock et al., 2000)[34]. In

[32] The assumed asset deprecation period is 10 years for mobile equipment such as motors and pumps, and 15 years for fixed installed equipment such as pipelines.

[33] In addition, investment loans – free of interest – are provided by the Swiss Federal Office for Agriculture to partially finance the remaining investment costs.

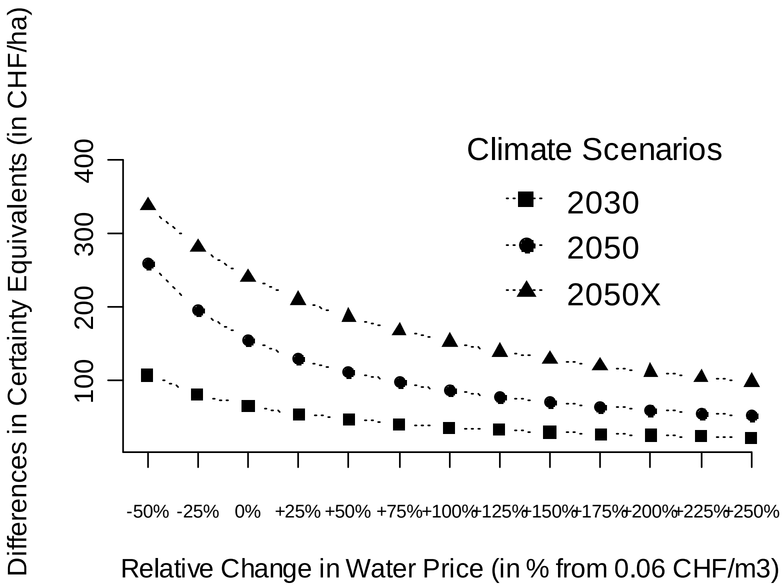
[34] In Switzerland, potential environmental damages of irrigation are limited to some extent due to strict obligations in agricultural cross compliance measures as well as in the bill on water protection.

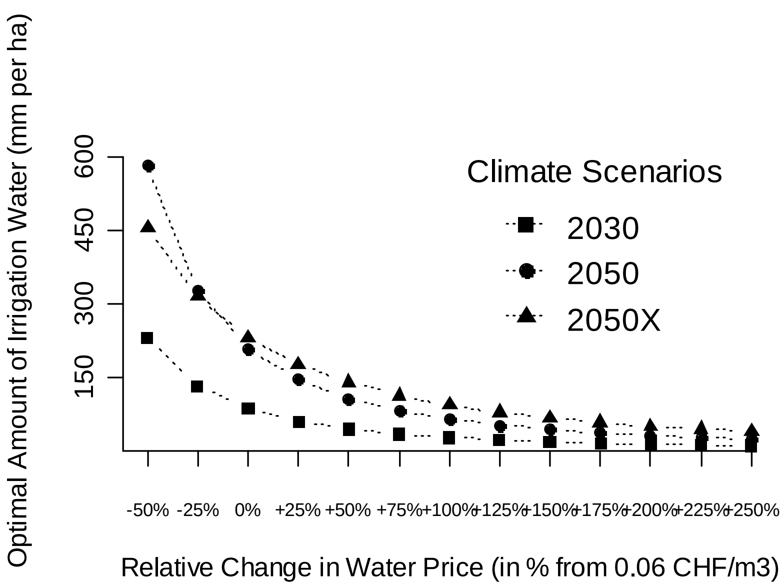
contrast, decreasing withdrawal prices might reflect further subsidization of pumping costs by providing support to electricity or fuel costs[35].

Figure 5.5 shows that decreasing water prices result in an over-proportional increase of the privately optimal amount of irrigation water applied per hectare. In contrast, increasing water prices gradually offset higher certainty equivalent levels in irrigated vis-a-vis rainfed maize production for all climate scenarios. In addition, the optimal amount of irrigation water sharply decreases for higher water prices. Thus, increasing water prices might outweigh climate change induced incentives for the adoption of irrigation in Swiss maize farming.

[35] Currently, Swiss farmers are partially exempted (via reimbursement) from fuel taxes.

Figure 5.5. Sensitivity analysis: changing water prices.





Note: Calculations are based on price scenario P2. 2030, 2050 and 2050X denote climate scenarios that are described in Table 5.1.

In contrast, the analysis of farmers' reactions to increasing irrigation water prices given in other studies show much more moderate irrigation water demand elasticities than indicated by our sensitivity analysis. In particular for low water prices, farmers' water demand may be much more influenced by other determinants — such as agricultural policy, product prices, and structural factors — than by the water price, (Garrido, 1999, Gómez-Limón and Riesgo, 2004). Moreover, higher water prices do not necessarily result in reduced water demand because farmers change their management practice (e.g. adjusting the timing of operations) and cropping patterns (e.g. using crops with lower water requirements) instead. Water price increases might even lead to – counterintuitive – increases in the water demand. Higher water prices can induce the adoption of more efficient irrigation technologies that increase marginal benefits of water use and thus increase the water demand (Garrido, 1999).

In our model, water is assumed to be allocated perfectly, without any losses, for instance, due to runoff. Depending on the irrigation system (e.g. flood-, sprinkler-, or drip-irrigation), the water use efficiency of irrigation (i.e. the ratio of net irrigation water and the amount of water that has to be withdrawn) might be substantially smaller in reality than our implicitly assumed value of 1 (cf. Zilberman et al., 1997). Hence, the marginal productivity and thus the economic benefits of irrigation are overestimated in our model. Moreover, short and long-term on-farm damages of irrigation such as salinization, nutrient leaching or erosion are not considered in our model. In other words, the dynamic processes of irrigation-induced losses of soil productivity are not considered here. As a consequence, long-term benefits of irrigation are overestimated.

To overcome these shortcomings, future research shall address the issues of technological choice and investments in irrigation systems as well as the irrigation-induced dynamics of soil productivity. Moreover, the role climatic extreme events such as heat waves and droughts (see Fuhrer et al., 2006, Schär et al., 2004) need to be considered in an extension of our integrated assessment model that combines biophysical and economic approaches. Furthermore, this should be combined with an approach that is based on a geographic information system (cf., Döll, 2002, Liu et al., 2007) to map the expected impacts of climate change on crop production at the Swiss Plateau under consideration of site-specific soil and climatic properties.

Because average soil and climatic properties are considered in our model, the presented results reflect average impacts of climate change on maize production that might underestimate site-specific impacts of climate change due to differences, for instance, in soil, climatic and production conditions. This needs to be particularly taken into account when assessing the role of irrigation as a farmers' adaptation strategy to climate change.

5.4 Conclusions and Policy Recommendations

The impact of climate change on the maize production at the eastern Swiss Plateau is expected to be small if simple adaptation options such as shifts in sowing dates and adjustments in the production intensity are taken into account. Decreasing yield levels in rainfed farming systems must only be expected from rather extreme climatic changes. But, rainfed maize production might face increasing yield variability in the future.

To cope with these threats of increasing yield variability and possible decreases in yield levels, irrigation constitutes a further adaptation option which farmers might adopt. In maize farming, it increases yield levels and decreases yield variability under current and future climate conditions. The differences in yield levels and yield variability between irrigated and rainfed farming systems will be even higher with more pronounced climatic changes. But, the expected economic benefits of adopting irrigation will be rather small in the future, particularly if lower crop prices due to market liberalization are taken into account. Indeed, our analysis shows that the economic benefits of the adoption of irrigation in Swiss maize farming are not only sensitive to changes in climatic conditions but also to the development of output and water prices.

Furthermore, the adoption of irrigation farming will be influenced by the development of governmental support. Currently, up to 50% of the investment costs are covered by national and cantonal bodies. Thus, changes in institutional and market conditions rather than changes in climatic conditions will influence the future development of maize production in general, and the adoption of irrigation in particular. Accordingly, technological developments (Ewert et al., 2005) and the evolution of agri-environmental policies (Finger, 2008b) might also far outweigh climate change induced effects on crop production. Thus, strategic designs and valuations of long-term investments in irrigation facilities and capacities have to simultaneously consider combinations of climate, market and institutional risks.

Our results suggest furthermore that an expansion of governmental support for irrigation systems in maize farming systems – e.g. by higher shares of costs coverage or by less restrictive allocation practices – might not be necessary for the entire eastern Swiss Plateau region. Rather, a combination of other adaptation measures at the field and farm level can help farmers to benefit from climate change and to reduce the need for irrigation in Swiss maize production. In order to stabilize or increase yield and income levels, farmers might use, for instance, shifts in sowing dates, production intensity adjustments, changes in fallow and tillage practices, as well as changes and diversifications in cropping patterns. Moreover, higher production and income risks might be covered with farm income diversification and with financial market instruments such as insurances or weather derivatives (Risbey et al., 1999, Smit and Skinner, 2002, Torriani et al., 2008).

The subsidization of irrigation systems might even lead to an inefficient use of other adaptation measures even though these other measures might be more cost effective and less environmental harmful. For instance, the adoption of an alternative crop that is more suitable for warm and dry climatic conditions might be hindered if maize irrigation systems are subsidized. Any governmental support should take potential crowding-out effects into account if different strategies that reduce future production risks are assessed and compared. This requires a comprehensive assessment of the costs and benefits of irrigation projects and the development of adequate policy frameworks. Such assessment should comprise economic, social and environmental dimensions (e.g., Riesgo and Gómez-Limón, 2006). A systematic development of national and cantonal strategies is required that can benefit from experiences of other countries in supporting irrigation and water pricing. In particular, policies that affect new irrigation projects[36] should be based on some basic prerequisites that are developed by Garrido (2002) and can be summarized as follows:

New irrigation projects should be mainly financed by the users, not by the governmental bodies. Accordingly, only projects that are financially viable on their own should be considered by the farmers. In addition, any subsidization should be transparent and based on clear evaluations that include also environmental impacts and resource sustainability issues. Water pricing should be based on full cost recovery (including environmental damages) and take opportunity costs of water use into account.

[36] An increasing demand for irrigation facilities in the future is particularly expected in Swiss vegetable, fruit and potato production due to climatic changes and increasing quality requirements (Bravin et al., 2008, Weber and Schild, 2007)

Following these principles, government policies can encourage the efficient use of water and lower environmental damages and pollution in the future and guide farmers in selecting the most appropriate and economically efficient adaptation strategies to climate change.

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Chapter 6

Conclusion and Outlook

In this thesis, climate change impacts and potential adaptation measures in cereal production at the Swiss Plateau have been addressed. To this end, an integrated assessment model that combines biophysical and economic modeling approaches was developed. This model has been applied to analyze several adaptation options assuming different climate change and price scenarios. While policy recommendations developed in this thesis are presented in chapter 5, the main results and conclusions can be summarized in the following points:

- Compared to ordinary least squares estimation, the application of robust regression for the estimation of crop production functions reduces the differences between functional forms with respect to optimal input application. The use of robust regression can furthermore improve the applicability of crop production functions due to the more precise and reliable estimation of yield response processes in the presence of exceptional crop yield observations.
- The integration of biophysical and economic models using production and yield variation functions is a valuable tool for climate change impact assessment. This approach inherits good descriptions of crop physiological processes of the employed biophysical model CropSyst, and can furthermore integrate farmers' incentives to react on changes in climatic conditions. Thus, it enables the simultaneous analysis of climate change scenarios as well as of scenarios for changes in socioeconomic conditions such as price levels and farmers' risk aversion.
- For the time horizon considered in this analysis (2030-2050), climate change might, ceteris paribus, increase winter wheat yields slightly but negatively affect maize productivity at the eastern Swiss Plateau. However, simple adaptation options such as shifts in sowing dates, adjustment of production intensity and the adoption of irrigation farming are sufficient to generate higher and less variable maize and winter-wheat yields in the future.

- In maize farming systems at the eastern Swiss Plateau, climate change increases the differences in optimal input application and yield variability between soils with different contents of soil organic matter. Impacts of climate change and optimal adaptation actions are thus site- but in particular soil-specific. Therefore, changes in climatic conditions are expected to increase the profitability of (and thus farmers' incentives to adopt) site specific management practices.
- Taking shifts in sowing dates and the adjustment of production intensity into account, the impact of climate change on rainfed maize productivity at the eastern Swiss Plateau is small for the considered time horizon (2030-2050). According to our results, moderate climate change is expected to increase yield levels slightly but increase yield variability. Slightly decreasing yield levels are only indicated if rather extreme climate change scenarios are assumed.
- At the eastern Swiss Plateau, the adoption of irrigation farming increases yield levels and decreases yield variability in maize production. Thus, it might be an adaptation option to cope with decreases in yield levels and increases in yield variability potentially caused by climate change. However, the profitability of irrigation farming remains small, in particular if price decreases due to market liberalization in Switzerland or higher water prices are considered.
- Not the expected changes in climatic conditions but rather changes in institutional arrangements (e.g. future design of subsidies) and market conditions (e.g. future development of price levels) will influence the development of Swiss cereal production in general and the adaptation decisions taken by the farmers' (such as the adoption of irrigation farming) in particular. Moreover, future technological development and the future structure of agri-environmental policies might also far outweigh climate change induced effects on Swiss cereal production.

Throughout the chapters of this thesis, several directions for future research are suggested that have not been addressed in climate change impact and adaptation studies for Switzerland yet. The most important suggestions are summarized in the following points:

- Because climate change impacts are highly site- and soil specific, future research should combine integrated assessment models and geographic information system based approaches (taking into account site-specific soil-, climatic-, and production-conditions) to improve the knowledge on the spatial distribution of impacts and potential adaptation to climate change in Swiss crop production.

- In order to validate the results of existing studies, additional climate change scenarios should be applied in impact assessment models. In addition, these climate scenarios should emphasize the increasing frequency of climatic extreme events such as droughts and heavy rainfalls.
- Modeling approaches describing farmers' and stakeholders' potential adaptation and adjustment reactions to climate change should be improved by using better representations of decision making processes.
- Further adaptation options should be integrated in existing models. In particular adaptation strategies to higher frequencies of climatic extreme events that are based on agronomic adaptation measures or financial market instruments should be considered.
- Impact assessment should be based rather on dynamic farming systems (i.e. including crop rotations and dynamics in soil and nutrient cycles) than on static analysis for individual crops. This enables a more realistic description of farmers' adaptation potentials and economic impacts of climate change.
- Attempts should be made to better understand the feedback processes between the communication of climate scenarios, impact expectations of farmers, governmental support to adaptation, agricultural policy arrangement, changes in market conditions, and technological development in the future. An improved understanding of the entire scientific, economic, and political system can increase the benefit of climate change related research on agriculture for the society.

In conclusion, this thesis shows that in the next decades climate change will have small positive effects on Swiss cereal production. However, climate change impacts might differ widely between different crops and locations. Thus, the assessment of site- and crop-specific impacts as well as the development of optimal adaptation responses and strategies to climate change need further attention in future research.

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